INVESTIGATING THE FACTORS THAT INFLUENCE SOUTH AFRICAN CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

by

CLAUDETTE RABIE

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Supervisor: Prof J.A. Wiid
Co-supervisor: Prof M.C. Cant

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DECLARATION

Name: Claudette Rabie
Student number: 5085-324-4
Degree: Doctor of Philosophy in Management Studies

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I further declare that I have not previously submitted this work, or part of it, for examination at Unisa for another qualification or at any other higher education institution.

I further declare that ethical clearance to conduct the research was obtained from the Research Ethics Review Committee of the Department of Marketing and Retail Management (see Annexure B), University of South Africa. I also declare that the research study was carried out in strict accordance with the Policy for Research Ethics of the University of South Africa. Great care was taken to ensure that the research study was conducted with the highest integrity, taking into account the University's Policy on Infringement and Plagiarism.

CRabie
Signature

1 February 2024
Date

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ABSTRACT

INVESTIGATING THE FACTORS THAT INFLUENCE SOUTH AFRICAN CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

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Mobile shopping apps have gained popularity among consumers in the digital age. With the rise of the on-demand economy and increased use of mobile phones and apps, the demand for same-day delivery has increased substantially. In response, retailers have turned to mobile shopping apps to meet consumers' demands for quick and efficient service. However, there is limited research on consumers' behavioural intention to continue using same-day delivery apps in South Africa, where the on-demand economy is still emerging. Understanding the factors that drive the adoption of same-day delivery apps is critical for businesses looking to succeed in the evolving digital landscape.

To fill this research gap, a research study was conducted to develop and test a consolidated technology acceptance model within the South African context. The Unified Theory of Acceptance and Use of Technology (UTAUT2) Model served as the guiding foundation of the conceptual model, which was extended with four exogenous mechanisms (constructs) to investigate its significance in relation to South African consumers' behavioural intention. Generational cohort (age) and gender were investigated as moderators of the study's variables.

A deductive, quantitative research approach was adopted within the ambit of the post-positivistic research paradigm. Furthermore, to achieve the research objectives, a cross-sectional survey design was applied. Data were collected through a web-based self-administered questionnaire from a sample of 485 South African consumers residing in Gauteng, KwaZulu-Natal and the Western Cape province. The study found that the model explained an estimated 70.8% of the variance in behavioural intention, with perceived customer value (a new construct which emerged) being the only construct with a significant influence. Moderation analysis revealed that generational cohort and gender had a minimal impact on the relationship between perceived customer value and behavioural intention. No statistically significant differences were evident between individuals from different demographic backgrounds.

The research study offers a unique and reliable behavioural intention model for using same-day delivery apps in a South African context, shedding light on the factors that influence consumers' intention to continue using same-day delivery apps. The research findings can guide the development of effective strategies to promote the adoption and use of same-day delivery apps in a South African context. Recommendations were offered to businesses already operating in the on-demand realm and to those looking to venture into the same-day delivery app industry.

Keywords:

Acceptance of technology; behavioural intention; food delivery apps; mobile apps; on-demand economy; retail; same-day delivery apps; South Africa; Unified Theory of Acceptance and Use of Technology (UTAUT2) Model; use behaviour

OPSOMMING

’N ONDERSOEK NA DIE FAKTORE WAT SUID-AFRIKAANSE VERBRUIKERS SE GEDRAGSVOORNEME BEÏNVLOED OM STEEDS SELFDEDAGAFLEWERINGSTOEPASSINGS TE GEBRUIK

deur
Claudette Rabie

Mobiele-inkopietoepassings het in die digitale era baie gewild by verbruikers geraak. As gevolg van die opkoms van die op-aanvraagekonomie en die toenemende gebruik van selfone en toepassings, het die vraag na selfdedagaflewerings aansienlik gestyg. In reaksie hierop het kleinhandelaars hulle na mobiele-inkopietoepassings gewend om te voldoen aan die verbruikers se vraag na vinnige en doeltreffende diens. Daar bestaan egter beperkte navorsing oor verbruikers se gedragsvoorneme om steeds selfdedagafleweringstoepassings in Suid-Afrika te gebruik waar die op-aanvraagekonomie steeds groei. Dit is van kritieke belang vir ondernemings wat in die ontwikkelende digitale landskap suksesvol wil wees om die faktore te verstaan wat die aanvaarding van selfdedagafleweringstoepassings aanmoedig.

Ten einde hierdie navorsingsleemte te vul, is 'n navorsingstudie onderneem om 'n gekonsolideerde tegnologie-aanvaardingsmodel vir die Suid-Afrikaanse konteks te ontwikkel en te toets. Die Model vir die Verenigde Teorie van Aanvaarding en Gebruik van Tegnologie (*Unified Theory of Acceptance and Use of Technology – UTAUT2*) het as rigtinggewende grondslag van die konseptuele model gedien, wat uitgebrei is met vier eksogene meganismes (konsepte) om sy belangrikheid met betrekking tot Suid-Afrtikaanse verbruikers se gedragsvoornemens te ondersoek. Generasiekohort (ouderdom) en -geslag is as moderators van die studie se veranderlikes nagevors.

’n Deduktiewe, kwantitatiewe navorsingsbenadering is in die sfeer van die post-positivistiese navorsingsparadigma gevolg. Vervolgens is 'n deursnee-opnameontwerp gebruik ten einde die navorsingsdoelwitte te bereik. Data is deur middel van 'n webgebaseerde, selftoegediende vraelys ingesamel met behulp van 'n steekproef van 485 Suid-Afrikaanse verbruikers wat in Gauteng, KwaZulu-Natal en die Wes-Kaap woonagtig is. Die studie het bevind dat die model ongeveer 70.8% van die variansie in gedragsvoorneme verduidelik, met waargenome klantewaarde ('n nuwe konsep wat ontstaan het) wat die enigste konsep was met 'n noemenswaardige invloed. Modereringsontleding het aangetoon dat generasiekohort en -geslag 'n minimale uitwerking op

die verhouding tussen waargenome klantewaarde en gedragsvoorneme het. Geen statisties-beduidende verskille is tussen individue uit verskillende demografiese agtergronde gevind nie.

Die navorsingstudie bied ’n unieke en betroubare gedragsvoornememodel om selfdedag-afleweringstoepassings in 'n Suid-Afrikaanse konteks te gebruik, wat lig werp op die faktore wat verbruikers se voornemes beïnvloed om steeds selfdedagafleweringstoepassings te gebruik. Die navorsingsbevindings kan die ontwikkeling van doeltreffende strategieë rig om die aanvaarding en gebruik van selfdedagafleweringstoepassings in 'n Suid-Afrikaanse konteks te bevorder. Aanbevelings word gemaak aan ondernemings wat reeds werksaam is in die op-aanvraagterrein asook aan diegene wat van voorneme is om die terrein van selfdedagafleweringstoepassing te betree.

Sleutelwoorde:
Tegnologie-aanvaarding; gedragsvoorneme, kosafleweringstoepassings; mobiele toepassings; op-aanvraagekonomie; kleinhandel; selfdedagafleweringstoepassings, Suid-Afrika; Model vir die Verenigde Teorie van Aanvaarding en Gebruik van Tegnologie; gebruiksgedrag

ISISHWANKATHELO

UPHANDO NGEMIBA ECHAPHAZELA INJONGO YABATHENGI BOMZANTSI AFRIKA YOKUQHUBEKA UKUTHENGA KWII-APPS EZIHAMBISA IODOLO NGEMINI UMNTU ATHENGE NGAYO

ngu
Claudette Rabie

Ii-apps (okanye iziza) zentengiso ziya zithandwa ngokuthandwa ngabathengi kweli xesha ledijithali. Njengoko lusanda uqoqosho lokunxulumanisa ubuchwepheshe bedijithali neenkonzo ezidingekayo nokwanda kokusetyenziswa kweefowuni eziphathekayo kunye nee-apps, imfuneko yokuhambisa iodolo ngosuku ekuthengwe ngalo yandile kakhulu. Ukusabela kwizidingo zabathengi, abathengisi babhenela kwii-apps zentengiso ezisezifownini eziphathwayo ukuze kusetyenzwe ngokukhawuleza nangokwanelisayo. Noxa kunjalo, lusalabalaba uphando lweenjongo zabathengi zokuqhubeka ekuthengeni kwii-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo eMzantsi Afrika, apho uqoqosho lokunxulumanisa ubuchwepheshe bedijithali neenkonzo ezidingekayo lusavelayo. Kubaluleke kakhulu ukuqonda ngemiba eqhuba ukusetyenziswa kwee-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo ukuze amashishini aphumelele kule mihla yedijithali.

Ukuze kuvalwe esi sikhewu kuphando, kwaqhutywa isifundo sophando ngenjongo yokuvelisa nokuvavanya indlela yokusebenzisa ubuchwepheshe obunzulu kwiimeko zoMzantsi Afrika. Ingcingane okanye ithiyori eyi *Unified Theory of Acceptance* kunye nemodeli eyi *Use of Technology (UTAUT2) Model* zasetyenziswa njengesiseko esikhokela le modeli icetywayo, neyathi yandiswa ngeentsika zobungqina obungaphandle ezine ngenjongo yokuphanda ukubaluleka kwale modeli kwiinjongo zabathengi boMzantsi Afrika. Kwasetyenziswa ubudala bokuzalwa nesini njengeempawu zokuthelekisa iyantlukwano yeenjongo nokuziphatha kubathengi.

Kwasetyenziswa indlela yophando eqwalasela ubuninzi bamanani ekufikeleleni kwisigqibo, oko kusenziwa ngokulandela icebo lophando apho ubuyena bomphandi buchaphazela iingcinga nezimvo zakhe. Ngaphaya koko, ukuze kufezekiswe iinjongo zophando, kwasetyenziswa uhlolo zimvo zokuqwalasela abathathi nxaxheba ngaxeshanye. Kwaqokelelwa idatha ngokusebenzisa uludwe lwemibuzo apho umthengi wayeziphendulela ngokwakhe, kubathengi boMzantsi Afrika ababengama-485 nababehlala eGauteng, KwaZulu-Natal naseNtshona Koloni. Isifundo

safumanisa ukuba imodeli yacacisa ukuba ama-70.8% aqikelelweyo eyantlukwano kwiinjongo nokuziphatha kwabathengi, nexabiso lemveliso kumthengi elaye labonakala (kwavela ubungqina obutsha) nobaye yabubo bodwa obunefuthe elivakalayo. Uhlalutyo ngokuthelekisa ifuthe leempawu ezahlukeneyo lwadiza ukuba ubudala nesini bunefuthe elingephi kubudlelwane phakathi kokuxabiseka kwemveliso kumthengi nenjongo equka ukuziphatha kwakhe. Akuzange kuvele mahluko umandla phakathi kwabathengi abavela kuluntu lweendawo neentlanga ezahlukeneyo.

Esi sifundo sophando sivelisa imodeli ekhethekileyo nefana yodwa yokuziphatha nenjongo yomthengi yokusebenzisa ii-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo kwimeko yoMzantsi Afrika. Ikwadiza nemiba enefuthe kwiinjongo zomthengi zokusebenzisa ii-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo. Okufumaniseke kuphando kungakukhokela ukuphuhliswa kwamacebo okuqhubela phambili nasekusetyenzisweni kwee-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo kwimeko yoMzantsi Afrika. Kwanikwa iingcebiso kumashishini asele eqhuba apho adingeka khona nakulawo asafuna ukungena kweli candelo lee-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo.

Amagama aphambili:
Ukwamkeleka kobuchwepheshe; injongo nokuziphatha; ii-apps zokuhambisa ukutya; ii-apps zefowuni ephathwayo; uqoqosho lokunxulumanisa ubuchwepheshe bedijithali neenkonzo ezidingekayo; urhwebo; ii-apps zokuhambisa iiodolo ngemini ekuthengwe ngayo; uMzantsi Afrika; Ingcingane eyi-Unified Theory of Acceptance kunye nemodeli eyi-Use of Technology (UTAUT2); ukuziphatha ekusebenziseni

LIST OF ABBREVIATIONS

CFA	Confirmatory factor analysis
CMB	Common Method Bias
COVID-19	Coronavirus disease
C-TAM-TPB	Combined Technology Acceptance Model and Theory of Planned Behaviour
DOI	Diffusion of Innovation
D-TPB	Decomposed Theory of Planned Behaviour
EFA	Exploratory factor analysis
GDP	Gross domestic product
GFI	Goodness-of-fit index
IDT	Innovation Diffusion Theory
MM	Motivational Model
MPCU	Model of PC Utilisation
R^2	Squared multiple correlation
SCT	Social Cognitive Theory
SEM	Structural equation modelling
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT/2	Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

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CHAPTER 1:
SCIENTIFIC ORIENTATION TO THE RESEARCH STUDY

1.1 INTRODUCTION

Over the last two decades, the retailing landscape has undergone a significant transformation, with conventional in-store shopping being replaced by several technological innovations and advancements. Consumers have a wide range of platforms and opportunities at their disposal, owing to having constant access to high-speed Internet, growth in smartphone ownership and sophisticated personalised and interactive mobile applications (or apps) (Belanche, Flavián & Pérez-Rueda, 2020: 1). Along with the expansion of the smartphone market, the mobile app market is accelerating in growth (Musakwa & Petersen, 2023: 2). Modern life is largely dependent on mobile apps as smartphone users can freely select, download and install apps that satisfy their demands and lifestyle (Song, Jeon & Jeon, 2017: 37).

Chapter 1 introduces the study by presenting the background to and rationale for the research study. Insights are provided into the development of mobile shopping apps, the rise of the on-demand economy and the demand for same-day delivery apps, as a result of the worldwide COVID-19 pandemic. The research problem is then stated, followed by a brief literature review explicating the underlying theoretical paradigm and research model supporting the study. Subsequently, the research question, objectives and statement of significance are presented. The research methodology, which lends structure to the research process, is formulated and the delimitations are discussed. Finally, the manner in which the chapters are presented concludes Chapter 1.

1.2 BACKGROUND TO THE RESEARCH STUDY

In March 2020, the world went into lockdown after the World Health Organization (WHO) declared the coronavirus disease (COVID-19) outbreak a pandemic, given the severity of its impact globally (WHO, 2020). Each sector of the economy experienced turmoil due to lockdown regulations, temporary housing arrangements, social distancing measures and travel restrictions. Supply chains worldwide encountered severe disruptions and had difficulties adapting to the changing needs of a locked-down world (Musakwa, 2021: 1). While demand soared in certain categories, it plummeted in others. Organisations were considering significant strategic changes to the setup and operation of their supply chains as they battled to keep their businesses afloat (Alicke,

Barriball & Trautwein, 2021: 2). Consequently, the need for businesses to expand into the online domain and offer home deliveries increased considerably (Daniel, 2021; Deloitte, 2021: 5; Zhu, Chou & Tsai, 2020: 6).

During the COVID-19 pandemic era, the demand for home deliveries has risen, with China's online mobile delivery service orders surging by 20% in January 2020 alone (Musakwa, 2021: 2). Additionally, with the increasing number of individuals having access to a smart device with Internet connectivity, the trend towards m-commerce has grown. Environmental circumstances and lifestyle preferences have had an impact on consumers' buying requirements and behaviours, shifting them to a world where mobile devices reign. The portability and time effectiveness permitted by mobile devices allow customers to purchase products and/or services whenever they want, wherever (Bhavsar, 2018). These behavioural changes have led to the adoption of a 'mobile first' business approach, which means that mobile platforms can no longer be ignored. Therefore, to maintain a competitive advantage and attract a larger audience, retailers must constantly adapt to the needs and desires of consumers in the new 'always on' technological era. Online marketplaces and businesses have therefore established the profitable 'on-demand economy' to quickly meet customers' demands for products, services, or information (Vaidya, 2023).

The burgeoning on-demand economy, or 'access economy', which enables consumers to order a variety of products and services from the convenience of their own homes using a smart device, has transformed the nature of modern trade (Zhong, 2021: 158). Hanks (2018) describes the on-demand economy as an economic activity developed by digital marketplaces and technology companies to satisfy customer demand through quick access to products and services. Through an online marketplace where individuals can effortlessly sell and buy products and services without time restrictions, the on-demand economy strives to give users immediate access to products and services (Jain, 2022). Uberisation, which started as the fastest way to hail a taxi, has changed the way businesses perceive demand, provision the supply and deliver (Vyas, 2023). Since then, a variety of on-demand services have emerged, including transportation and travel, food delivery, grocery delivery, healthcare, fitness, entertainment, beauty salons, learning and professional services (Faisal, 2021; Vilmate, 2021; Vyas, 2023). The food and grocery on-demand market, or same-day delivery market, was the focus of this research study.

On-demand service apps are used to a greater extent in economic activities, enabling both large and small businesses to reach a wider client base and draw in both young and old (Zhong, 2021:

158). Same-day delivery apps, or on-demand food and grocery delivery apps[1], are mobile platforms that allow users to order products with independent service providers or intermediaries and receive the ordered products on the same day the order was placed. Same-day delivery apps aim to reduce the delivery time of orders to the same day to give customers instant gratification (Jain, 2022). According to Zhong (2021: 158), the on-demand economy attracted more than 22.4 million American users who spent US$57.6 billion using various on-demand service apps in 2020. Moreover, the market for on-demand services is expected to reach US$335 billion by 2025 (PWC, 2015: 14; Vyas, 2023). More specifically, the online food and grocery delivery market is experiencing significant growth and is expected to reach US$401,391 in market value by 2025, at an annual rate of 8.74% (Gorbatch, 2022).

Hattingh and Ramlakan (2022: 6) state that despite the expansion of m-commerce and the on-demand economy globally, brick-and-mortar stores remain the key channel for shoppers in South Africa, although online shopping has become more popular over the past few years. Picodi (2019) reports that South Africans prefer to shop online using desktop computers rather than smartphones, with only 33% of online transactions taking place in the country in 2019. According to a study by Deloitte (2021: 6), only 15% of consumers intended to shop online for groceries, whereas 51% intended to shop online from restaurants or fast-food outlets. In another study, it was reported that clothing/apparel (53%), entertainment/education (digital/downloadable) (51%) and event tickets (51%) were the most popular online shopping categories for South African consumers (Davis, 2019: 4). Many South African consumers (63%), according to Musakwa and Petersen (2023: 2), purchased groceries online for the first time because of the COVID-19 pandemic and movement restrictions enforced by government. Even though there has been an increase in Internet sales, the majority of South African consumers still make in-store purchases (Makhitha, Van Scheers & Mogashoa, 2019: 313). Despite the worldwide increase in delivery service apps, many organisations have not yet adopted these apps, particularly in developing countries such as South Africa (Musakwa & Petersen, 2023: 2).

The above discussion leads to the question: Why do South African shoppers not actively use mobile devices to purchase products, and more specifically from same-day delivery apps, considering the expansion of the m-commerce industry and the burgeoning on-demand retail market? As South Africans are increasingly starting to use mobile apps to shop (Deloitte, 2021: 8), retailers must understand the reasons for consumers not using same-day delivery apps to

[1] It is acknowledged that the term ‘on-demand delivery apps’ is also used to refer to same-day delivery apps. In the literature search, both terms were used, but the term *same-day delivery apps* is used in this research study.

purchase products and recognise the factors that are likely to influence their behavioural intentions to continue using same-day delivery apps.

1.3 RATIONALE FOR THE RESEARCH STUDY

Several scholars have explored the acceptance and use of mobile shopping apps globally, but few have focused on same-day delivery apps, especially in a developing country such as South Africa. Elango, Dowpiset and Chantawaranurak (2019), for example, combined constructs from the Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM) to explore the factors that might impact users' behavioural intention to use on-demand food delivery apps in Bangkok. An integration of the Unified Theory of Acceptance and Use of Technology (UTAUT2) Model and Diffusion of Innovation (DOI) theory was employed by Yapp, Balakrishna, Yeap and Ganesan (2018: 105) to determine the factors that drive the intention to adopt on-demand services among male and female technology users in Malaysia. The UTAUT2 Model and DeLone and McLean's Information Systems Success Model were integrated and used by Erwanti, Widodo and Nurhayati (2018: 9) to examine the factors that influence the continuance intention to use a specific on-demand mobile service app (GO-JEK) in Indonesia. These research studies report that perceived self-efficacy, perceived usefulness, social influence, facilitating conditions, hedonic motivation, habit, price value, satisfaction and perceived risk significantly influence the acceptance of on-demand delivery service apps (Elango et al., 2019: 12; Erwanti et al., 2018: 9; Yapp et al., 2018: 105). In a more recent study, Groß (2022: 38) explored the drivers and barriers to adopting ultra-fast grocery delivery apps, or on-demand grocery services, by German consumers. Groß (2022: iii) identifies convenience, peer group behaviour, general perception, a good assortment of products and curiosity as the main drivers of acceptance. The main barriers to the adoption of on-demand grocery services were found to be the lack of on-site experience and inspection, personal value motives and missing use instances (Groß, 2022: 38).

In South Africa, two related studies could be found pertaining to the adoption of on-demand or same-day delivery service apps. The first was by Fatoki (2020) who investigated the intention of university students to use smartphones for grocery shopping by applying the TAM. Theoretically, Fatoki's study confirms the applicability of TAM in predicting behavioural intention in respect of the use of mobile technology for m-commerce. Empirically, the findings show that perceived usefulness and perceived ease of use positively affect both attitude and intention towards online grocery shopping (Fatoki, 2020: 5). The second study that was found was by Musakwa. In a qualitative study, Musakwa (2021: 8) examined the factors affecting consumers' acceptance of one specific grocery-related same-day mobile delivery app in South Africa, namely Checkers

Sixty60. Musakwa (2021: iii) employed the UTAUT2 Model as a theoretical base to qualitatively analyse 4 159 Google Play Store customer reviews about the Checkers Sixty60 app, using thematic content analysis. The results reveal that performance expectancy, effort expectancy, facilitating conditions and hedonic motivation prominently affected the use of this same-day delivery mobile app.

As is evident from the discussion above, none of the aforementioned studies investigated which factors influence South African consumers' behavioural intention to continue using a variety of food- and grocery-related same-day delivery apps by quantitatively utilising and extending the UTAUT2 Model. While Fatoki applied TAM, Musakwa explored the acceptance of one specific grocery-related same-day delivery app through qualitative measures. This current research study quantitatively explores the factors that influence the acceptance and continuous use of various food- and grocery-related same-day delivery apps. It therefore addresses this gap in the literature.

1.4 PROBLEM STATEMENT

The burgeoning m-commerce industry and on-demand economy have fuelled the development and widespread adoption of various digital platforms, including same-day delivery apps. Despite their growing popularity, research examining the acceptance and continuous use of these apps, especially in developing countries like South Africa, remains limited (Van Niekerk, 2020: 9; Vyas, 2023; Zhong, 2021: 158). Existing studies have primarily focused on developed countries, neglecting to capture the unique contextual factors that influence consumer behaviour in emerging markets (e.g. Amin, Arefin, Sultana, Islam, Jahan & Akhtar, 2020; Arsiwala, 2020; Belanche, Casaló, Flavián & Pérez-Rueda, 2021; Benhardy & Ronadi, 2020; Choi, 2020; Chotigo & Kadono, 2021; Flores & Castaño, 2020; Muangmee, Kot, Meekaewkunchorn, Kassakorn & Khalid, 2021; Rasli, Zulkefli, Salleh, Ghani, Razali & Idris, 2020; Salleh, Hamir, Azmi & Siddiqe, 2020; Song, Ruan & Jeon, 2021; Zhao & Bacao, 2020). This presents a significant gap in the understanding of how same-day delivery apps are perceived and utilised in the South African context.

The lack of contextual understanding impedes the generalisability of findings and limits the ability to fully grasp the broader adoption and impact of same-day delivery apps. Existing theoretical models, such as the UTAUT2 Model, however, may not fully encompass the multifaceted dynamics of the South African market, warranting further adaptation and extension. Existing technology adoption models were primarily developed in developed countries and may not adequately account for the cultural, economic and technological complexities of emerging markets like South Africa. This further necessitates the adaptation and extension of existing models to

incorporate context-specific variables that accurately represent the unique dynamics of the South African market.

Additionally, while existing studies have identified key factors influencing same-day delivery app acceptance, there is limited understanding of the underlying mechanisms and processes that drive these relationships (Elango et al., 2019; Erwanti et al., 2018; Fatoki, 2020; Musakwa, 2021; Yapp et al., 2018). Exploring various exogenous mechanisms that influence consumers behavioural intention to continue using same-day delivery apps can provide deeper insights into consumer behaviour and decision-making processes, particularly in the context of emerging markets.

By addressing these critical gaps and unresolved questions, this research aims to make significant contributions to the understanding of consumer acceptance and continuance use of same-day delivery apps in South Africa. The findings will provide valuable insights for app developers, retailers, and policymakers in optimising their strategies and catering to the evolving needs of South African consumers. Ultimately, this research will contribute to the advancement of same-day delivery apps in developing economies and enhance the overall efficiency and convenience of the m-commerce landscape.

1.5 RESEARCH QUESTION AND OBJECTIVES

The research problem guided the development of and gave rise to the following general research question, from which the specific research objectives were derived:

Research question: What factors influence South African consumers' behavioural intention to continue using same-day delivery apps?

1.5.1 PRIMARY OBJECTIVE

From the research question, the primary research objective was formulated, and secondary research objectives were set in terms of the literature review and empirical study.

The **primary research objective** was to examine the factors influencing South African consumers' behavioural intentions to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model.

1.5.2 SECONDARY OBJECTIVES

The following specific research objectives were formulated for the literature review and the empirical study.

1.5.2.1 Literature review

In terms of the literature review, the specific secondary research objectives were formulated as follows:

Research objective 1: To discuss mobile apps and same-day delivery app usage from an international and South African context and in relation to the retailing industry.

Research objective 2: To assess the scientific and methodological rigour of the UTAUT2 Model to position an improved theoretical paradigm to use the model as the foundational framework for the research study.

Research objective 3: To identify, in the literature, theoretically and empirically validated constructs that significantly influence consumers' behavioural intention towards new technology.

Research objective 4: To conceptualise the identified constructs and investigate the theoretical interrelationships between the independent constructs and behavioural intention, relevant to the context of the research study.

Research objective 5: To identify and conceptualise the moderating constructs (generational cohort and gender) and investigate their effect on the independent constructs and behavioural intention.

Research objective 6: To develop a conceptual model based on the theoretical relationship dynamics between the independent constructs, the moderating effects and behavioural intention.

1.5.2.2 Empirical study

In terms of the empirical study, the specific secondary research objectives were formulated as follows:

Research objective 1: To explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market.

Research objective 2: To explore the suitability of the individual items measuring the latent constructs in the research instrument involving a sample of South African consumers.

Research objective 3: To assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention.

Research objective 4: To examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers.

Research objective 5: To evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model.

Research objective 6: To empirically assess the interaction effects between the independent variables and the dependent variable, and two demographic conditions (moderators), namely generational cohort and gender.

Research objective 7: To assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps.

Research objective 8: To formulate conclusions and make recommendations for the marketing and retailing industry, and for possible future research, based on the results of the research study.

1.6 THEORETICAL PARADIGM AND RESEARCH MODEL

Since the 1980s, academics across a myriad of contexts and settings have been interested in exploring how consumers adopt and use new technological devices, systems and services (Van Niekerk, 2020: 12). Several renowned theories have been proposed in recent years to explain the relationship between users' attitudes, beliefs and behavioural intention to use technological devices or information systems (Tarhini, El-Masri, Ali & Serrano, 2016: 832). From the social psychology stream, the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM), and Innovation Diffusion Theory (IDT) are only a few of the major modular approaches that have led the way in analyses and results (Tarhini et al., 2016: 832). These technology acceptance and adoption behaviour theories and models aim to explain how individuals may understand and use new technology (Momani & Jamous, 2017: 51).

Selecting the most appropriate theory in adoption behaviour research remains crucial for researchers (Al-Mamary, Al-Nashmi, Hassan & Shamsuddin, 2016: 143) because different models have different premises and benefits for predicting behavioural intention (Samaradiwakara & Gunawardena, 2014: 29). The UTAUT2 Model, however, has proven to be more robust in assessing and predicting adoption behaviours as it combines the foundational works of eight leading and competing technology acceptance theories, namely IDT, Social Cognitive Theory (SCT), TRA, TAM, TPB, the Model of PC Utilisation (MPCU), the Motivation Model (MM) and a model combining TAM and TPB (C-TAM-TPB).

Previous technology acceptance models, such as Bandura's SCT, have faced criticism for overlooking individual emotions and biological influences. SCT's cognitive focus fails to account for personality changes over time and struggles to define constructs like self-efficacy clearly (Van Niekerk, 2020: 105). Similarly, the IDT effectively explains user adoption of innovative technologies but encounters difficulties with non-quantifiable features and treats consumers uniformly across adoption spectrums (Van Niekerk, 2020: 95). The TRA, while widely used in determining behavioural intention, falls short in scenarios involving multiple alternatives and behaviours beyond an individual's control. Its combination of beliefs also limits a clear understanding compared to other models like the TAM (Persson & Berndtsson, 2015: 11; Miladinovic & Xiang, 2016: 13). Ajzen's TPB incorporates perceived behavioural control but neglects adaptive cognitive learning and habitual behaviour aspects, impacting its suitability for technology acceptance studies (Leung & Chen, 2017: 1639). Similarly, the TAM has been criticised for its simplicity, lack of consideration for external factors (such as social influence and economic factors), and inability to predict mobile technology usage effectively (Lièbana-Cabanillas, Marinković & Kalinić, 2017: 15; Persson & Berndtsson, 2015: 20; Ratten, 2015: 27; Shafinah, Sahari, Sulaiman, Yusoff & Ikram, 2013: 129). These limitations collectively led to their exclusion as foundational models for this research study, which aims for a comprehensive understanding of same-day delivery app adoption.

The UTAUT Model was first validated and published by seminal authors Venkatesh, Morris, Davis and Davis in 2003. Intended for organisational or employee technology adoption research, the UTAUT Model was developed to predict user adoption and offer managers a valuable tool to assess the likelihood of whether the implementation of new technology will be successful (Venkatesh et al., 2003: 426). The model provides organisations with a better understanding of the numerous factors that influence the adoption of new technology in the workplace, enabling managers to proactively design interventions that are aimed at users that might be less inclined to adopt new technologies in an organisational setting (Venkatesh et al., 2003: 426).

Eight well-known technological acceptance models were thoroughly examined and compared by Venkatesh et al. (2003: 426), which led to the development of a unified model that incorporates components from all eight of these models and theories. Empirical analysis and validation revealed four main constructs that explain users' intentions to use an information system and subsequent usage behaviour in an organisational setting, namely performance expectancy, effort expectancy, social influence and facilitating conditions. In addition, Venkatesh et al. (2003: 447) posit that gender, age, experience and voluntariness of use moderate the impact of the four main constructs on usage intention and behaviour. The UTAUT Model is shown in Figure 1.1.

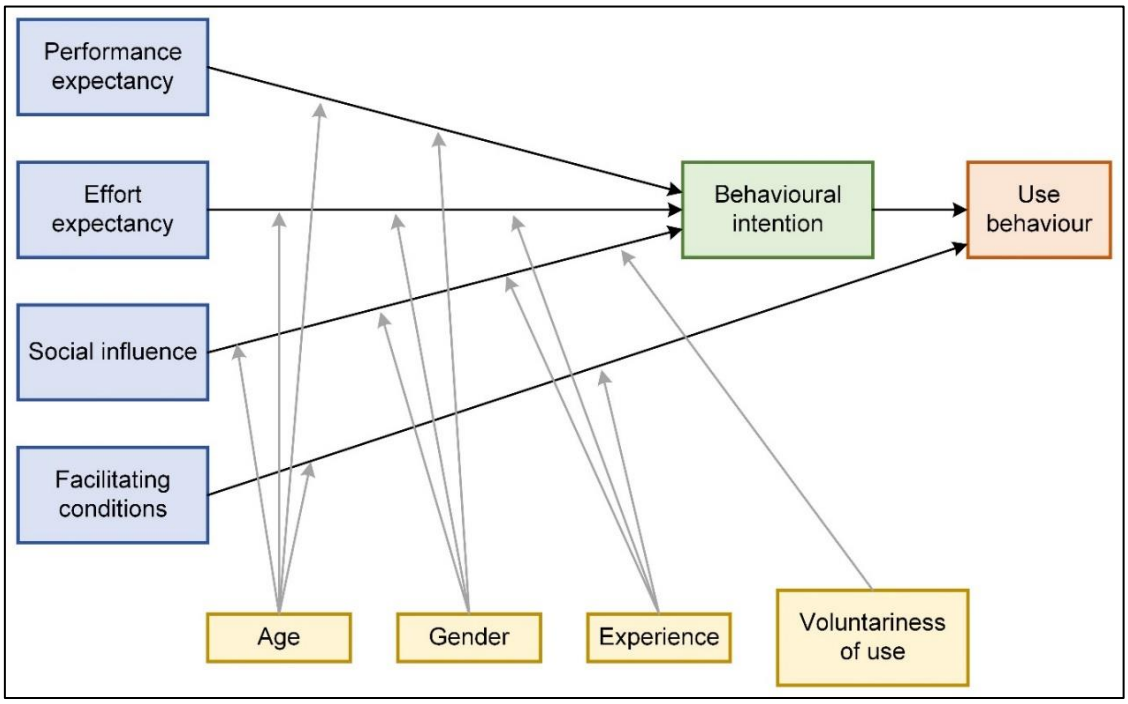

Figure 1.1: The Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh et al. (2003: 447)

At the centre of the model, Venkatesh et al. (2003: 447) theorised behavioural intention as a predictor of technology usage behaviour (in Thomas, Singh & Gaffar, 2013: 72). Behavioural intention is defined as "… a person's likelihood or subjective probability to engage in a given behaviour" (CHIRr, n.d.). Therefore, behavioural intention is an individual's tendency to engage in a given behaviour and reflects their readiness and willingness to try to accomplish a particular behaviour (Ajzen, 1991: 181). The UTAUT Model maintains that performance expectancy, effort expectancy and social influence affect the behavioural intention to use technology, while facilitating conditions and behavioural intention to use technology are determinants of actual or planned technology use (Miladinovic & Xiang, 2016: 15; Williams, Rana & Dwivedi, 2015: 444).

In 2012, the UTAUT2 Model was created by Venkatesh et al. (2012: 158) to enhance the UTAUT Model for a consumer use context. While the originally published UTAUT Model focused on assessing technology adoption and usage behaviour by employees in an organisational context, the UTAUT2 Model was developed primarily to study consumer technologies and explain consumers' acceptance and adoption behaviours (Gupta & Dogra, 2017: 147; Miladinovic & Xiang, 2016: 16). The UTAUT2 Model is a theory that incorporates three additional constructs and interactions significant to technology adoption research, namely hedonic motivation, price value and habit, as illustrated in Figure 1.2.

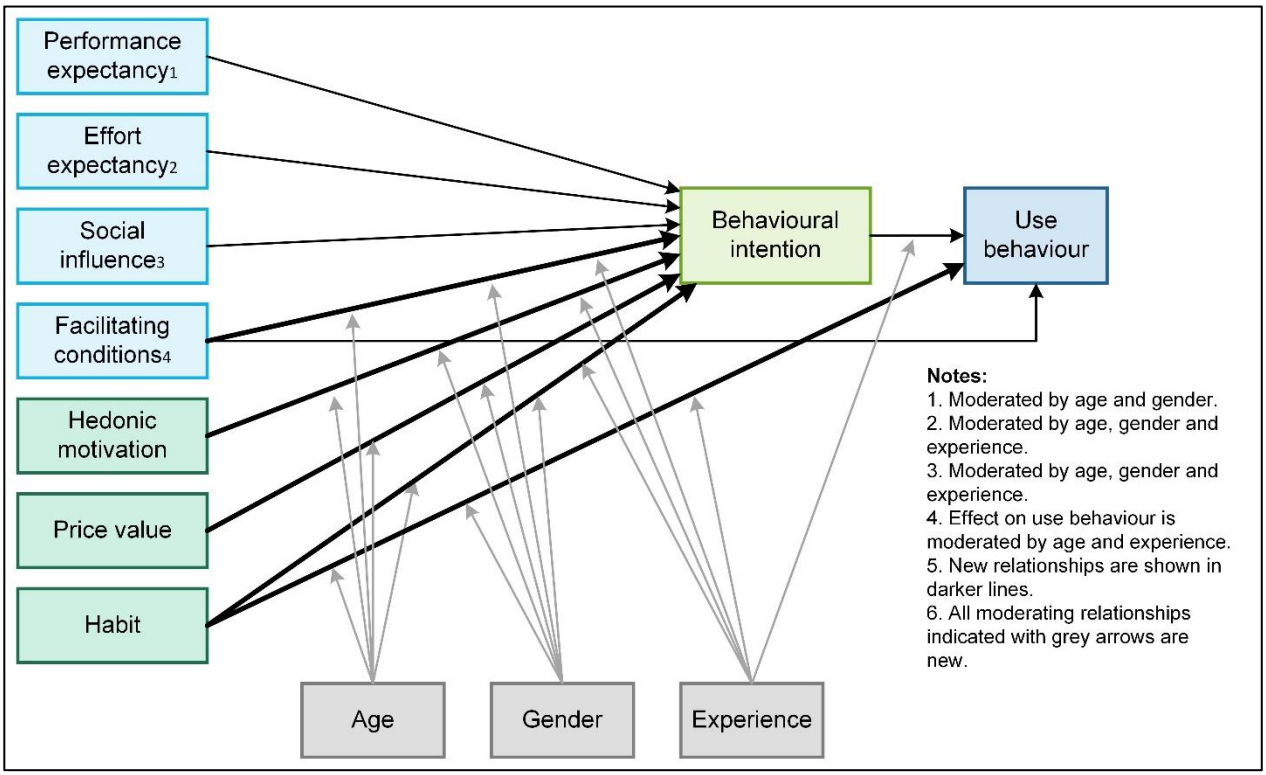

Figure 1.2: The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)
Source: Venkatesh et al. (2012: 160)

The UTAUT2 Model includes the same four constructs as identified and validated in the initial UTAUT Model, namely performance expectancy, effort expectancy, social influence and facilitating conditions, albeit differently applied and moderated to a consumer context (Goulão, 2014: 6). Three additional constructs that are important to the investigation of consumer acceptance and use of technology were added to the UTAUT2, namely hedonic motivation, price value and habit (Venkatesh et al., 2012: 160). These constructs are further moderated by age, gender and experience. The moderating construct, voluntariness of use, was excluded from the

UTAUT2 Model since consumers' behaviours are completely voluntary and consumers are not obligated to use the technology in question (Goulão, 2014: 6).

The UTAUT2 Model served as the cornerstone of the conceptual model proposed for this research study. The reason is that the UTAUT2 Model has been shown to outperform earlier technology acceptance models and theories (Dwivedi, Rana, Jeyaraj, Clement & Williams, 2017: 719; Gharaibeh & Arshad, 2018: 125; Moghavvemi, Salleh & Abessi, 2013: 247; Taiwo & Downe, 2013: 48; Van Niekerk, 2020: 22). 74% of the variance in the UTAUT2 Model is explained by behavioural intention, compared to the 56% of variance found in the original UTAUT Model. For mobile Internet users, Rondan-Cataluña, Arenas-Gaitán and Ramírez-Correa (2015: 797–798) assessed the explanatory power and goodness-of-fit indices for a variety of technology acceptance models, including the TRA, variants of TAM, UTAUT and UTAUT2. The results showed that the UTAUT2 had the best model fit and quality indices compared to the other models, and it explained the most variance (64%) in behavioural intention.

The UTAUT2 Model provides empirical support for the applicability of the model in the consumer context, and its suitability, validity and reliability to explain technology adoption in various contexts have been supported by numerous studies (e.g. Bühler & Bick, 2013; Gruzd, Staves & Wilk, 2012; Hew, Lee, Ooi & Wei, 2015; Tak & Panwar, 2017; Tan, Lee, Lin & Ooi, 2017). The UTAUT2 is a complex model with many constructs and is therefore not perceived to be trivial, restricted in explanatory and predictive power, to have questionable empirical value, or to lack any practical value (Trojanowski & Kutak, 2017: 95). It is evident that the UTAUT2 Model is more robust in assessing and predicting behavioural intention and actual behaviour in a consumer context (Dwivedi et al., 2017: 719; Moghavvemi et al., 2013: 247; Taiwo & Downe, 2013: 48), and has more explanatory power than other competing models (Gharaibeh & Arshad, 2018: 125). How effectively the UTAUT2 satisfies Weber's framework and criteria (2012) for evaluating a theory will be discussed in Chapter 3.

The UTAUT2 Model has also been applied in several contexts, and numerous researchers have provided extensive empirical evidence to validate the model's theorised relationships (e.g. Baptista & Oliveira, 2015; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Gupta & Dogra, 2017; Nair, Ali & Leong, 2015). In the realm of m-commerce, mobile shopping and mobile shopping app research, the UTAUT2 Model has proven to be successful in describing behavioural intention (e.g. Chopdar & Sivakumar, 2019; Fadzil, 2017; Lee, Sung & Jeon; 2019; Mensah, 2019; Rasli et al., 2020; Sair & Danish, 2018; Van Niekerk, 2020; Zhao & Bacao, 2020). However, it remains

underutilised in exploring consumers' behavioural intention to use on-demand mobile services, such as same-day delivery apps, as reiterated in sections 1.2 to 1.4 above.

The UTAUT2 Model provided the foundation for the research study's conceptual model (refer to Figure 1.3 below). As the research study investigated the constructs that influence consumers' behavioural intention to continue using same-day delivery apps in South Africa, the UTAUT2 Model was considered to be well suited to this research study. The following section highlights the proposed research model and constructs pertinent to the research study and context.

1.6.1 RESEARCH MODEL

As previously stated, the proposed conceptual model was built on the foundation of the UTAUT2 Model for parsimony, as recommended by Venkatesh, Thong and Xu (2016: 346). An adaptation of the UTAUT2 Model was suggested for testing in the research study. The UTAUT2 Model's main effects, which served as the theoretical basis for measuring consumers' behavioural intention to continue using same-day delivery apps, were implemented, namely performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value. The research study further extended the UTAUT2 Model by incorporating four additional exogenous mechanisms (or constructs): lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use, which were identified through a thorough literature search. Furthermore, it was proposed that generational cohort (age) and gender will affect the interaction between the independent and dependent constructs. The research study thus offers a methodical analysis and theorising of salient factors that may be applied in the context of consumers' technology usage behaviours and contributes to the body of knowledge on intention behaviour research.

The proposed conceptual model for the research study is shown in Figure 1.3. The UTAUT2 Model that underpins the conceptual model is represented in the figure by light blue boxes, and its extension to include four theoretically validated exogenous mechanisms are represented by green boxes. The moderating effects are illustrated by the grey boxes and arrows in Figure 1.3.

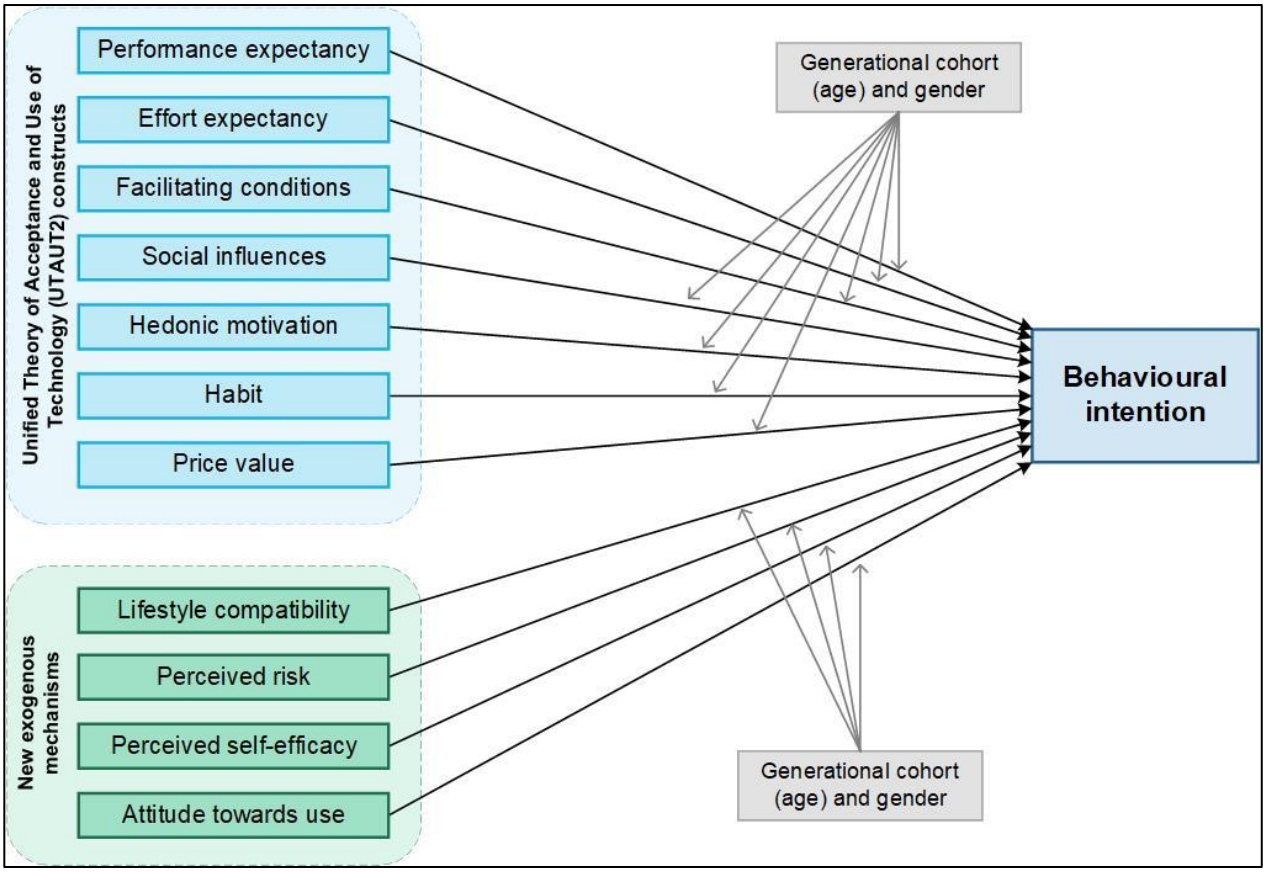

Figure 1.3: Conceptual model and the theoretical interrelationship between constructs
Source: Author's own compilation

1.6.2 CONSTRUCTS

Each of the constructs proposed in the conceptual model shown in Figure 1.3 is further explained in the sections that follow. A detailed description of each construct, and its relevance to the research study, is discussed in Chapter 4.

1.6.2.1 Performance expectancy

Performance expectancy is defined by Venkatesh et al. (2012: 159) as "… the extent to which using a specific technology benefits the consumer who carries out a particular activity." Performance expectancy, in the context of the research study, refers to how much an individual believes that using same-day delivery apps would offer them an advantage in performing a specific task in everyday situations (Huang & Kao, 2015: 5). Same-day delivery apps have the advantage of saving time and effort as individuals can conveniently shop any time and anywhere. It also means that users can simply open the app and immediately find what they are looking for. With mobile apps, users may be able to accomplish their personal goals successfully and efficiently

(Van Niekerk, 2020: 137). Another potential benefit, especially during the COVID-19 pandemic, was that the product would be delivered to the location of the user's choice in a short amount of time and the individual would not have to go to a brick-and-mortar store to purchase the product.

1.6.2.2 Effort expectancy

According to Venkatesh et al. (2003: 450; 2012: 159), effort expectancy relates to the ease with which a specific technology, gadget, or system is employed. Using new technologies is considered easy and convenient; Lee et al. (2019: 4) therefore claim that the greater the perceived ease of use, the greater the willingness to use the technology. Consumers would generally be more receptive to new technologies if they perceive that the particular technology is easy to use (Kang, Mun & Johnson, 2015: 212). In the context of the research study, effort expectancy refers to the degree to which users feel that their continued use of same-day delivery apps will be convenient, coherent, rational and free of any effort. Effort expectancy signifies the measure of ease that is associated with using a mobile app and how simple it is for consumers to utilise same-day delivery apps to make purchases, decide what to buy and order and receive goods quickly.

1.6.2.3 Facilitating conditions

The construct of facilitating conditions refers to a user's assessment of the resources and assistance offered when engaging in a specific behaviour or task (Venkatesh et al., 2012: 159). According to Venkatesh et al. (2003: 453), facilitating conditions are a personal belief that the organisational and technical infrastructure is in place to facilitate the use of technology. Facilitating conditions, in the context of m-commerce, refer to a smartphone with constant Internet access and a user with some knowledge and familiarity with the technology (Van Niekerk, 2020: 142). Consumers are more inclined to use the technology in question when they receive the necessary support (Venkatesh et al., 2012: 162). This is in line with Yang (2010: 267), who points out the significance of facilitating conditions in the acceptance and use of m-commerce by consumers.

1.6.2.4 Social influence

Social influences occur when an individual is exposed to other people's beliefs, attitudes, behaviours and sentiments which are viewed as acceptable social behaviours, whether consciously or unconsciously (Rashotte, n.d.). As a result, social influence refers to a consumer's perception that their family and friends expect them to adopt a certain technology (Venkatesh et

al., 2012: 159). Generally, individuals develop intentions towards a technology when they are inspired and encouraged to do so by significant others whose opinions they value.

1.6.2.5 Hedonic motivation

Hedonic motivation was first mentioned by Venkatesh et al. (2012: 161) in the development of the UTAUT2 Model and is defined as "… the fun or pleasure derived from using a technology". Hedonic motivations, which are derived from perceived enjoyment, are driven by an individual's emotional reactions, sensory pleasures, dreams and aesthetic preferences (Kusuma, Idrus & Djazuli, 2013: 242). Hedonic motivations, seen through the lens of mobile app users, refer to users' desires for the pleasure, amusement, or fun that comes with using a specific app (Mavuya, 2016: 17, 20). In information systems research, hedonic motivation has been shown to play an important role in determining technology acceptance behaviours (Alalwan, Dwivedi & Rana, 2017: 106; Brown & Venkatesh, 2005: 406; Uitz & Koitz, 2013: 130; Venkatesh et al., 2012: 161).

1.6.2.6 Habit

Introduced in the UTAUT2 Model, Venkatesh et al. (2012: 161) define a habit as the degree to which individuals tend to carry out a certain behaviour or utilise a particular technology automatically, as a result of learning and prior experience. A habit is an automatic, unconscious and involuntary behaviour that is goal-directed and serves a certain purpose (Kim, Malhotra & Narasimhan, 2005: 419; Limayem, Hirt & Cheung, 2007: 710-714). The more habitually a task is performed, the less choice is required, and the less influence external factors will have on consumers' usage behaviours (Miladinovic & Xiang, 2016: 24). Van Niekerk (2020: 31) argues that, in the current smartphone era, using a smartphone has become such routine that it is practically unconscious, and similar effects can be seen in other types of technology (Venkatesh et al., 2012: 161). For instance, according to Chou, Chiu, Ho and Lee (2013: 4), utilising apps promotes the development of new habits mostly because they are entertaining and make users' lives easier. A certain behaviour becomes more ingrained the more often it is practised or repeated (Van Niekerk, 2020: 31).

1.6.2.7 Price value

Venkatesh et al. (2012: 158) introduced a price or cost component when creating the UTAUT2 Model to establish behavioural intention from a consumer's point of view. Price value was added, since, in the context of consumer technology use, the cost is a crucial consideration because, in

contrast to workplace technologies, consumers are responsible for covering the costs of using technology (Venkatesh et al., 2012: 158). Price value is described as "… consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost of using it" (Venkatesh et al., 2012: 161). As a result, individuals seek out benefits they perceive as being greater than the financial loss associated with using the particular technology (Gupta, Dogra & George, 2018: 58). Contextually, same-day delivery apps have certain financial charges associated with them, such as the need for an Internet data bundle, a service and/or delivery fee imposed by the operator, store or restaurant and an optional gratuity for the driver. Consumers' intentions to utilise same-day delivery apps may be hindered by these fees that are associated with using the app.

1.6.2.8 Lifestyle compatibility

Lifestyle compatibility refers to the alignment of values and lifestyle preferences, and measures how well individuals believe a given technology fits into their way of life (Boateng, Adam, Okoe & Anning-Dorson, 2016: 471). This suggests that individuals tend to accept technologies that are consistent with their beliefs, values, social morals, past experiences and self-perception. A consumer's lifestyle is said to be compatible with same-day delivery apps if the user feels that they complement their way of life and social interactions. Consequently, lifestyle compatibility is defined in the context of the research study as the beliefs and values an individual holds regarding online shopping and how well the activity of online shopping fits into the consumer's lifestyle (Cuna, 2020: 9).

The importance of lifestyle compatibility has risen significantly as a result of the wide range of technological developments available to customers. Therefore, it is suggested and has been extensively investigated that an individual's intention to use a particular technological innovation may be affected by how well the technology fits into their lifestyle. Similarly, it is asserted that an individual's lifestyle is a reliable indicator of whether they will continue using same-day delivery apps. The significance of new technological breakthroughs being adaptable to an individual's lifestyle and daily routine is emphasised in adoption behaviour research, as empirical data supports the notion that lifestyle compatibility significantly influences individuals to adopt online shopping and various mobile apps (e.g. Arora & Malik, 2020: 98; Belanche et al., 2020: 14; Cuna, 2020: 4; Leung & Chen, 2017: 1639).

1.6.2.9 Perceived risk

Perceived risk is defined as "... a potential loss as perceived by a customer while shopping online using mobile retail apps when compared to purchasing products offline" (Kaushik, Mohan & Kumar, 2020: 12). According to Pauzi, Thoo, Tan, Muharam and Talib (2017: 5), perceived risk is also referred to as a person's level of uncertainty over the outcome of their decision in online purchasing. Contextually, therefore, perceived risk relates to the possible loss that a consumer perceives when shopping online or utilising mobile retail apps, as opposed to doing so in person.

Regardless of the exponential expansion of the mobile app market, technology presents several security and privacy issues that discourage the use of online shopping platforms (Belanche et al., 2020: 6). Individuals may be deterred from using online platforms because of a variety of risks associated with mobile apps, such as the inability to physically inspect a product, the potential loss of control over personal and/or payment information, the risk of having a stranger deliver the order, transaction fraud, waiting time to receive an order and the turnaround time of complaints lodged by the user (Dawi, 2019: 117; Pauzi et al., 2017: 5, Van Niekerk, 2020: 32). Even though same-day delivery apps have various advantages and opportunities, there is a high risk of privacy violations because users' personal information, such as their contact, location and payment information, must be shared and can be compromised (Yun, Han & Lee, 2013: 217). Individuals are thought to be discouraged from using mobile shopping channels like same-day delivery apps because of perceived risk (Van Niekerk, 2020: 148).

In the literature, perceived risk and security have received a great deal of attention as a factor that influences users' acceptance of new technological platforms, systems and devices (e.g. Chopdar, Korfiatis, Sivakumar & Lytras, 2018: 3; Hubert, Blut, Brock, Backhaus & Eberhardt, 2017: 181; Kaushik et al., 2020: 12). There is a wealth of literature suggesting a significant correlation between perceived risk and the intention to embrace or use new technology. Prior studies on mobile shopping apps confirms a negative correlation between behavioural intention for online shopping and perceived risk across several industries, including retail and m-commerce (e.g. Ali & Maideen, 2019: 375; Arora & Malik, 2020: 106; Kaushik et al., 2020: 12; Marriott & McLean, 2019: 19; Vasileiadis, 2014: 187; Verkijika, 2018: 1673). The literature indicates that perceived risk may operate as a detractor in the adoption process, in contrast to the driving factors in the UTAUT2 Model (Slade, Dwivedi, Piercy & Williams, 2015: 864). It is believed that using same-day delivery apps carries risks that could potentially prevent individuals from adopting these apps.

1.6.2.10 Perceived self-efficacy

Self-efficacy is defined in an organisational context as "… the assessment of one's ability to use a technology to perform a specific job" (Venkatesh et al., 2003: 432). Perceived self-efficacy is a person's perception of their ability to complete a certain activity utilising technology or mobile devices (Singh, Zolkepli & Kit, 2018: 115), which is argued to strongly predict behavioural intention and adoption behaviours. In the context of the research study, perceived self-efficacy refers to an individual's perception of their competence and confidence in their capacity to finish a certain activity or task utilising mobile apps (Hu & Zhang, 2016: 645; Yul, 2014: 12).

To establish self-efficacy in the context of mobile technology, measures have been developed by various scholars who found self-efficacy to be valid in predicting users' intention to adopt new mobile innovations (e.g. Islam, Khan, Ramayah & Hossain, 2011: 82; Jeong & Yoon, 2013: 35; Marriott, Williams & Dwivedi, 2017: 576; Okumus & Bilgihan, 2014: 39; Wu, Wang & Lin, 2007: 65; Wang & Wang, 2008: 405). According to theoretical validation, perceived self-efficacy is anticipated to have a considerable impact on consumers' behavioural intention to use mobile apps. Researchers have provided empirical data confirming that self-efficacy implicitly affects consumers' behavioural intention to adopt various types of mobile apps (Okumus & Bilgihan, 2014: 39; Wu et al., 2007: 65; Wang & Wang, 2008: 405), including the acceptance of on-demand product delivery apps (Elango et al., 2019: 13). It is argued that the more self-efficacious users view themselves to be, the higher their intention to use new technology will be (Okumus & Bilgihan, 2014: 39; Marriott et al., 2017: 576). This is in line with Islam et al. (2011: 82), who state that individuals with high perceived self-efficacy are more likely to adopt m-commerce successfully because they anticipate that the system will be user-friendly and simple to operate.

1.6.2.11 Attitude towards use

Attitude has long been a fascinating research topic in the field of marketing because it enables researchers and marketers to forecast consumers' intentions and purchase behaviours (Khanal, 2018: 7). Consumer behaviour is greatly influenced by consumers' attitudes (Makanyeza, 2014: 874). Thus, to fully comprehend consumers' behaviours, it is necessary to understand consumers' attitudes (Schiffman & Kanuk, 2004: 253). Contextually, consumer attitudes are described as "… the consistent tendency of consumers to behave, favourably or unfavourably, with regards to a specific product or brand" (Schiffman & Kanuk, 2004: 253). According to Makanyeza (2014: 874), understanding consumer attitudes is crucial since it enables marketers to foresee or predict consumers' behaviours.

Extensive research has been done in the fields of e-commerce and m-commerce on the relationship between the attitudinal construct and behavioural intention (e.g. Al-Debei, Al-Lozi & Papazafeiropoulou, 2013: 46; Heirman & Walrave, 2012: 614; Hu & Zhang, 2016: 652; Sanne & Wiese, 2018: 4; Thomas et al., 2013: 84). In addition, several academics who explored individuals' attitudes towards using food delivery apps found that these attitudes had a great impact on individuals' intentions to use these kinds of technologies (Cho, Bonn & Lee, 2018: 108; Lee, Lee & Jeon, 2017: 1468; Shukla & Sharma, 2018: 192; Troise, O'Driscoll, Tani & Prisco, 2021: 675). Specific research on the interaction between attitude towards use and behavioural intention in respect of same-day delivery apps, however, could not be found. Nevertheless, related literature provides supporting evidence that a consumer's attitude towards using a new technology would significantly predict their intentions towards using it (e.g. Cho et al., 2018: 108; Lee et al., 2017: 1468; Shukla & Sharma, 2018: 192; Troise et al., 2021: 675). Several studies have reported a strong empirical relationship between attitude and behavioural intention. Consequently, individuals tend to engage in a certain behaviour when they have a positive attitude toward that behaviour (Al-Debei et al., 2013: 46; Heirman & Walrave, 2012: 614; Sanne & Wiese, 2018: 4).

1.6.2.12 Moderators (generational cohort and gender)

In assessing how the UTAUT2 Model has been extended in various research studies, Venkatesh et al. (2016: 328) concluded that there is a gap in the literature regarding the effects of moderating factors, such as age and gender. Since individuals are likely to differ greatly from one another in terms of their beliefs, values, perceptions, or understanding of various constructs, research suggests that the UTAUT2 Model be tested with the inclusion of demographic characteristics (Ameen & Willis, 2018: 2; Dwivedi et al., 2017: 721; Trojanowski & Kutak, 2017: 97-98; Venkatesh et al., 2016: 328). Failure to consider the effects of heterogeneity may result in drawing incorrect conclusions and formulating invalid recommendations (Hair, Sarstedt, Ringle & Mena, 2012: 427; Trojanowski & Kutak, 2017: 97-98). As a result, the moderating effect of generational cohort (age) and gender was incorporated into the research study to examine the conceptual model in its entirety.

Researchers have reported key demographic differences, such as age and gender inequalities, as having a direct and moderating effect on consumers' behavioural intention and the adoption of new technologies (e.g. Chung, Park, Wang, Fulk & McLaughlin, 2010: 1675; Tarhini, Hone & Liu, 2014: 168; Venkatesh et al., 2003: 267; Wang, Wu & Wang, 2009: 97). The addition of age and gender as moderators would likely improve the explanatory power of technology acceptance and adoption behaviour research (Tarhini et al., 2014: 168). Murugesh-Warren et al. (2015: 1) agree,

stating that demographic differences are often an important consideration in academic research, particularly when investigating new technologies. As a result, while most studies contribute to a better understanding of the UTAUT2 Model's versatility in various contexts, there is still a need for a methodical analysis and theorising of salient factors that apply to the context of consumers' technology adoption behaviours (Venkatesh et al., 2012: 158).

The moderating effect of gender, age and experience was explored by Venkatesh et al. (2012: 159) in the UATUT2 Model. Experience as a moderator was not considered in the current research study because grocery-related same-day delivery apps were still relatively new in the South African market, and so users' experience with these types of apps might have been limited. In addition, the data used in the research study were cross-sectional rather than longitudinal (Pradhina & Pillai, 2020: 104). Experience is measured through time; a longitudinal study should therefore be conducted to investigate its effect on the interrelationship between the observed constructs. Age and gender were used as moderators in the research study to investigate consumers' behavioural intention to continue using same-day delivery apps.

In an effort to better understand how heterogeneity affects the connection between the independent and dependent variables, the research study theorised the moderating impacts of generational cohort and gender on consumers' behavioural intention to utilise same-day delivery apps. The potential moderators and their influence on the relationship between the independent variables and behavioural intention are elaborated upon in Chapter 4, section 4.2.13.4.

1.7 STATEMENT OF SIGNIFICANCE

Further research into the acceptance and use of various same-day delivery apps is required as it affects several stakeholders. From a theoretical perspective, an altered version of the UTAUT2 Model developed by Venkatesh et al. (2012: 157) was examined in this research study. The main effects of the UTAUT2 Model were applied in a different environment (the marketing and retailing industry), among new user groups and in a distinct cultural setting (South African consumers). A sample of South African consumers was used to examine the key effects of the UTAUT2 Model, including performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value.

The research study further adds to the body of knowledge through the extension of the UTAUT2 Model with four exogenous mechanisms to investigate their significance in relation to behavioural intention, namely perceived risk, lifestyle compatibility, perceived self-efficacy and attitude towards

use. The inclusion of the additional constructs was motivated by research demonstrating that these are key factors impacting consumers' use of m-commerce apps (e.g. Al-Debei et al., 2013: 46; Belanche et al., 2020: 6; Kaushik et al., 2020: 12; Makanyeza, 2014: 874; Marriott & Williams, 2018: 1; Moghavvemi et al., 2013: 247; Okumus & Bilgihan, 2014: 38; Pauzi et al., 2017: 1; Singh et al., 2018: 115; Thomas et al., 2013: 71; Vasileiadis, 2014: 187; Verkijika, 2018: 1673; Wang & Wang, 2008: 405).

Similar research investigating the adoption of various food- and grocery-related same-day delivery apps in South Africa and other developing African economies is limited. It was anticipated that the data gathered from testing the proposed conceptual model (see Figure 1.3) would contribute to the existing body of knowledge in this sector, offering insight on the adoption of same-day delivery apps in developing economies such as South Africa. From an industry or practical perspective, insights gathered from the research study will provide South African retailers, restaurants, app owners and app developers with a better understanding of the factors that influence South African consumers' intention to continue using food- and grocery-related same-day delivery apps. The results of the research study will therefore enable app developers and brand owners to enhance mobile delivery services by designing and developing a consumer-centric same-day delivery app.

1.8 RESEARCH METHODOLOGY

The research design and methodology employed in the research study followed a systematic process as adapted and collated from Bryman et al. (2014: 32), Kumar (2019: 43) and Saunders, Lewis and Thornhill (2019: 12) (refer to Figure 1.4 below). The research process commenced with the formulation of a research problem and objectives as given in sections 1.4 and 1.5 above, as well as a comprehensive review of the literature which yielded the conceptual model (presented in Chapters 3 and 4). Steps 3 to 7 of the research process represent the research design and methodology. The third step in the research process involves formulating the research design. This design, also known as the strategy of inquiry, serves as a framework guiding the collection and analysis of data in the research study. To address research questions or achieve objectives, the chosen research design is crucial (Bryman et al., 2014: 100; Saunders et al., 2019: 173).

The 'research onion' framework proposed by Saunders et al. (2018: 174) will be utilised to outline the structure of the research. This framework comprises six layers, starting from the outermost layer: research philosophy, approaches to theory development, methodological choices, research strategy, time horizons, and techniques and procedures. Each layer explores the researcher's decisions and choices, providing a comprehensive structure for the research process.

Subsequently, the population and sample for the research study are discussed and an outline of the sampling techniques and methods utilised is given. The instrument development process and procedures for data collection are then discussed as well as the data analysis procedures employed in the research study. The research design and methodology employed in the study are detailed in Chapter 5, and the research results are presented in Chapter 6. The research process is concluded in Chapter 7 in which conclusions are drawn from the results, limitations addressed and recommendations made to academia and the marketing and retail industry.

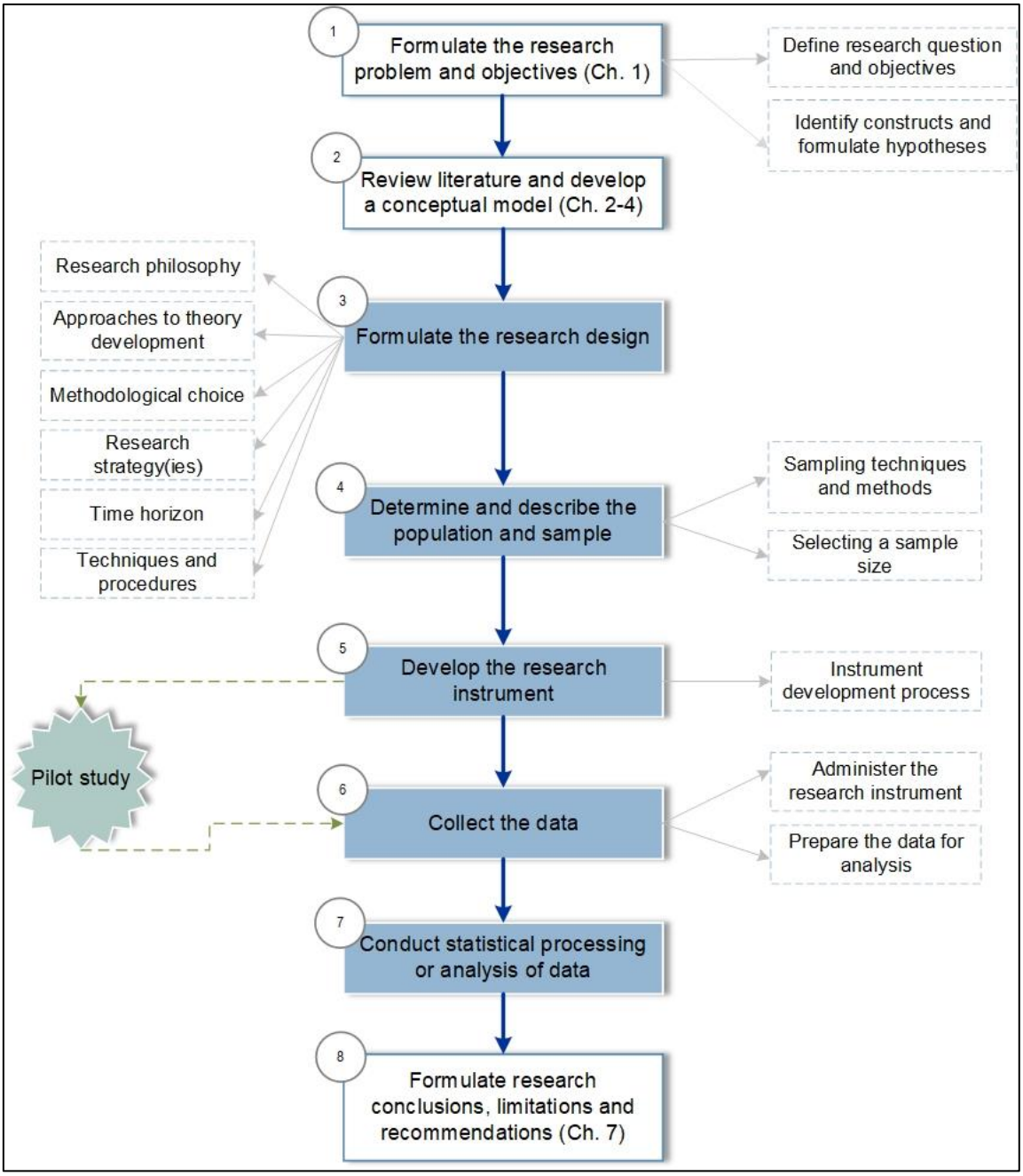

Figure 1.4: Research methodology process

Source: Adapted from Bryman et al. (2014: 32); Kumar (2019: 43); Saunders et al. (2019: 12)

1.8.1 RESEARCH DESIGN

The research study's design integrated both exploratory and descriptive elements to comprehensively investigate consumer attitudes and behaviours, particularly within the context of same-day delivery apps. Exploratory research was instrumental in refining the research scope, clarifying ambiguous problems, and developing theoretical frameworks and hypotheses. Conversely, descriptive research aimed to provide a detailed account of the characteristics and relationships between variables, addressing fundamental questions about the phenomenon under investigation.

The research adopted a post-positivist paradigm due to its acknowledgment of the limitations of a purely positivist approach in understanding consumer behaviour (Maksimović & Evtimov, 2023: 209). The post-positivist paradigm allowed for the exploration of the specific social and cultural contexts influencing consumers' reality. This paradigm facilitated a complex understanding of consumer behaviour, acknowledging that it is not always rational (Creswell & Creswell, 2018: 7; Goodyear-Smith & Mash, 2019). Furthermore, a deductive approach was adopted, aligning with the post-positivist paradigm (Venter & Van Zyl, 2017: 8). Adopting a deductive approach involved formulating hypotheses derived from existing theories and literature, empirically testing them, and refining the theory accordingly. The study aimed to quantitatively explain causal relationships between concepts and generalise results to the observed population.

Quantitative research, specifically a survey research strategy, was employed to achieve the research objectives. This approach, aligned with the post-positivist and deductive philosophy, allowed for the collection of numerical data to analyse relationships between variables (Venter & Van Zyl, 2017: 8; Saunders et al., 2019: 176). Survey research was chosen for its compatibility with a structured and controlled research process, suitability for exploratory and descriptive research, cost-effectiveness and statistical representativeness of the population. Within the realm of quantitative survey research, a cross-sectional survey design was selected to capture a snapshot of the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps at a specific moment in time. This design was deemed practical, cost-effective, and congruent with the exploratory and descriptive nature of the study.

In summary, the research design combined exploratory and descriptive research design, adopted a post-positivist paradigm and deductive approach, and implemented a cross-sectional quantitative survey research design. These methodological choices were justified based on their alignment with the research objectives, philosophy, and the need for a comprehensive

understanding of the factors influencing consumer behaviour in the South African context. The research design is thoroughly explained in Chapter 5 (see section 5.2.3).

1.8.2 TARGET POPULATION AND SAMPLE

The target population of the research study consisted of South African consumers, residing in either Gauteng, KwaZulu-Natal or the Western Cape provinces of the country. The sample was drawn from South African consumers who were between the ages of 18 and 65, owned a smartphone and made use of same-day delivery apps. Approximately 24.5 million South Africans, over a third of the population, were estimated to meet these criteria (O'Dea, 2020).

A non-probability sampling technique was adopted in the research study. Non-probability sampling is defined as a sampling design in which the likelihood of each unit being selected from the target population is unknown and members are selected from the population in a non-random manner (Saunders et al., 2019: 296; Venter & Van Zyl, 2017: 135). Given the large population and limitations in resources and time, a non-probability approach was deemed appropriate, especially considering the absence of an accurate sampling frame.

Convenience sampling, a form of non-probability sampling, was chosen to meet the research objectives of the study. In convenience sampling, individuals are chosen based on their availability and willingness to participate in the study (Saunders et al., 2019: 324; Zickar & Keith, 2023: 316). Participants are chosen for convenience sampling based on their likelihood to reply to the questionnaire itself. In an online, self-administered questionnaire, convenience sampling can be used to recruit participants quickly and easily from diverse backgrounds. This method is also cost-effective compared to other sampling methods, making it a popular option for researchers with restrictive resources. By using convenience sampling in an online questionnaire, researchers can efficiently collect data from many participants in a shorter amount of time.

To summarise, a non-probability convenience sample was selected from South African consumers who were between the ages of 18 and 65 years, resided in either Gauteng, KwaZulu-Natal or the Western Cape province, owned a smartphone and used same-day delivery apps. The sample of the research study comprised 485 South African consumers and was considered suitable to conduct the required statistical analyses and achieve adequate statistical power to detect practical effects by performing structural equation modelling (SEM), correlation analysis and moderation analysis. The population and sample are discussed in more detail in Chapter 5, section 5.2.4.

1.8.3 THE RESEARCH INSTRUMENT

To achieve the specific research objective of the study, and capture rich data, a well-designed research instrument had to be constructed. The instrument development process suggested by Barry, Chaney, Stellefson and Chaney (2011: 98) was followed to develop the instrument. The process was divided into four phases, namely outlining the constructs, developing the scale design and structure, generating sample items and pre-testing the scale, which included assessing the content or face validity, assessing cognitive and motivational quality, implementing a pilot study and lastly, finalising the research instrument.

After careful consideration of the constructs under investigation as well as the scale design, structure and individual scale items, the research instrument was assessed by a panel of expert reviewers and subjected to cognitive interviewing and a pilot study. A final and well-designed research instrument was developed.

The research instrument process is discussed in detail in Chapter 5, section 5.2.5.

1.8.4 DATA COLLECTION

Data were collected using a self-administered, online or web-based questionnaire facilitated by Springvale Online, an online marketing and data collection company. To achieve the primary research objective, approximately 400 validly completed responses from the three major metropolitans in South Africa, namely Gauteng, KwaZulu-Natal and the Western Cape, were required. This particular number was required to statistically validate the research instrument and conduct confirmatory analysis and SEM. Springvale Online offered a large database (≥ 40 000) of potential respondents dispersed across South Africa. Furthermore, they had the capacity, required equipment, hardware and software and knowledge to source responses from a representative sample that met the inclusion criteria of the research study. The role of Springvale Online was limited to distributing and obtaining valid responses. The responsibility to code, validate, clean and analyse the data lay with the researcher.

Springvale Online distributed invitations to participate in the research study to their database of consumers (members) via e-mail. The research instrument was loaded onto the online survey application used by Springvale Online, by an expert consultant. The e-mail contained information about the study's purpose, the participant's rights and the ethical clearance obtained for the research study. The URL link, contained in the e-mail, redirected the respondent to the online

survey application where they provided informed consent, confirmed their eligibility, and confirm that they understood the study's nature, procedure and their right to withdraw. Responses were automatically recorded on Springvale Online's system when the respondent completed the web-based questionnaire and raw data were exported to MS Excel for analysis.

A self-administered web-based questionnaire was deemed appropriate for several reasons: the target population included computer-literate individuals with access to both the Internet and e-mail, and the database primarily consisted of active online shoppers, increasing the probability of reaching respondents who used same-day delivery apps. Moreover, web-based questionnaires are distributed much faster, it is less expensive, have a shorter turnaround time and provide more flexibility compared to other data collection methods (Du Plessis, 2018: 192). Web-based questionnaires also ensure respondent anonymity and confidentiality.

A detailed account of the data collection procedures followed in the study are discussed in Chapter 5, section 5.2.6.

1.8.5 STATISTICAL PROCESSING AND ANALYSIS OF DATA

The statistical procedures applicable to the research study included univariate descriptive analysis (reporting of means, standard deviations, skewness and kurtosis), factor analysis, as well as inferential and multivariate analysis (including correlational analysis, SEM, moderation analysis and test for group mean differences). Statistical processes, such as confirmatory factor analysis (CFA) and SEM, were used to evaluate the performance of the individual items and constructs to further refine the measurement model.

Data analysis was conducted using IBM SPSS (version 28), as well as AMOS (version 27). Various statistical procedures were applied through SPSS which assisted in generating and delivering accurate statistical data that contributed towards the existing research field by offering improved knowledge regarding same-day delivery apps in South Africa. The data were analysed with the support of a professional statistician to ensure the quality and validity of the results.

The various statistical and analysis techniques used in the study as discussed in Chapter 5, section 5.2.7.

1.9 DELIMITATIONS

The following are the delimitations of the research study:

- The study was confined to research dealing with the constructs of behavioural intention, the UTAUT2 Model's constructs (performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivations, habit and price value) and four additional exogenous mechanisms (perceived risk, perceived self-efficacy, lifestyle compatibility and attitude towards use).
- The study was restricted to South African consumers residing in Gauteng, KwaZulu-Natal and the Western Cape provinces, who owned a smartphone and who used same-day delivery apps.
- The research study was cross-sectional.
- A non-probability sampling method was employed, resulting in the findings not being generalisable to the broader population. However, the purpose of the research study was not to generalise the findings, but rather to develop a model combining the factors that influence consumers' behavioural intention to continue using same-day delivery apps in a South African retailing context.
- Control variables were limited to generational cohort (age), gender and ethnic orientation. Furthermore, no attempt was made to alter or categorise any of the information, results or data based on marital status, occupation or disposable income categories.

1.10 CHAPTER LAYOUT

The chapter outline below paints a holistic picture of the remainder of the thesis. The research study comprises seven chapters, as summarised below.

Chapter 1: Scientific orientation to the research study

Chapter 1 introduced the study and outlined the background to and rationale for the research study, the problem statement, the research objectives, and the contribution of the results at a theoretical and practical level. A brief literature discussion lay the foundation for the research study and summarised the conceptual model developed for the purpose of the study. The research

design and methodology applied to achieve the primary objective of the research study were presented. Chapter 1 concludes with an outline of the delimitations to the study.

Chapter 2: The South African retail industry and the advent of m-commerce

Chapter 2 provides the metatheoretical context of the study that formed the definitive boundary of the research study. It offers context with a discussion of the South African retailing industry as well as the advancements of e-commerce, m-commerce and the mobile app market, with a specific focus on the emergence of the on-demand economy and the relevance of same-day delivery apps in the South African market. The significance and performance of same-day delivery apps globally and locally are debated to provide context to the study.

Chapter 3: The Unified Theory of Acceptance and Use of Technology Models (UTAUT and UTAUT2)

Chapter 3 provides a thorough assessment of the development of the Unified Theory of Acceptance and Use of Technology Models (UTAUT and UTAUT2) (Venkatesh et al., 2003; 2012), which served as the foundational framework on which the conceptual model for the research study was built. The constructs of the UTAUT and UTAUT2 Models and the moderating variables are discussed, and a theoretical analysis is offered of the credibility, validity and limitations of the model. The purpose of Chapter 3 is to assess the scientific and methodological rigour of the UTAUT2 Model and to establish its significance in determining consumers' behavioural intention in the milieu of the research study.

Chapter 4: Theoretical integration, proposed theoretical framework and hypotheses development

Chapter 4 offers the theoretical validation and integration of the conceptual model, measuring consumers' behavioural intention to continue using same-day delivery apps. The constructs identified from several scholarly works and empirically validated results are addressed, which have proven to be key determinants in establishing consumers' behavioural intention in various contexts. A theoretically grounded conceptual model for consumers' behavioural intention to continue using same-day delivery apps in a South African context is presented in Chapter 4.

Chapter 5: Research methodology

The research design and methodology applied in the study are explained in detail in Chapter 5. The research paradigm and approach, the research design, sampling methods and techniques,

data collection methods and analysis are explained using a detailed research process. The development of the research instrument, its administration as well as the statistical processing and analysis of data are described. Chapter 5 concludes with a discussion of the ethical principles and guidelines adhered to during the course of the research study.

Chapter 6: Research findings

The results emanating from the empirical research are presented and discussed in Chapter 6 to ascertain whether the research objectives of the study have been achieved.

Chapter 7: Conclusions, limitations and recommendations

Chapter 7 concludes the research report with the main findings of the literature review and the empirical results. Conclusions are provided in conjunction with each of the secondary literature and empirical research objectives from which recommendations are made to academia and the marketing and retail industry. The limitations of the research study are highlighted and further recommendations are made. Chapter 7 concludes with an evaluation of the research study by highlighting the contribution the study makes at a theoretical, empirical and practical level.

1.11 CONCLUSION

In Chapter 1, the scientific orientation of the research study was outlined. The chapter provided an in-depth introduction and background to the burgeoning on-demand industry and the lack of research on same-day delivery apps, especially in an emerging market such as South Africa. Even though the m-commerce sector and the on-demand economy are rising, research in these fields is still scarce. The lack of research on food- and grocery-related same-day delivery apps in South Africa has therefore raised the question as to why South African consumers do not use their mobile devices to purchase products from same-day delivery apps, considering the expansion of the m-commerce industry and the expanding on-demand retail industry. The research study therefore sought to identify the constructs that influence consumers' behavioural intention to continue using same-day delivery apps in South Africa. It is anticipated that insights gathered from the research study will contribute to the existing body of knowledge. The findings will help South African m-commerce business owners in better understanding the factors that influence consumers' behavioural intention to continue using same-day delivery apps, allowing them to adjust their business strategy accordingly.

In Chapter 2, a global and local perspective will be taken to explore the online retailing environment and its remarkable transformation from e-commerce to specialised m-commerce shopping apps. The development of same-day delivery apps and the introduction of e-commerce and m-commerce are examined in detail, along with how the retail industry in South Africa has changed over time.

CHAPTER 2:
THE SOUTH AFRICAN RETAIL INDUSTRY AND THE ADVENT OF M-COMMERCE

2.1 INTRODUCTION

Globally, the traditional landscape of retailing has shifted from solely physical store shopping to online and mobile shopping channels, allowing businesses to reach markets that are no longer constrained by time or space (Mkhosi, 2017: 5). Online retailing (or e-tailing) is one component of the wider digital transformation of the economy. Although e-tailing currently only accounts for a small part of all retail purchases, these sales are becoming increasingly significant globally, and mobile shopping apps are expanding quickly as a result (Goga, Paelo & Nyamwena, 2019: 1).

The online retailing environment and its rapid expansion from e-commerce to m-commerce and advanced mobile shopping apps will be explored from a global and local perspective in Chapter 2. A detailed account of the evolution of the retail industry in South Africa is provided, and the advent of e-commerce and m-commerce, with specific emphasis on the emergence of the growing on-demand economy and same-day delivery mobile apps market, is discussed. The chapter commences with an overview of the South African retail landscape by contextualising retailing and retailers in terms of the overall retail supply chain, followed by a description of the various retail sectors that make up the South African retail industry. Thereafter, a brief history of the rise and evolution of e-commerce and m-commerce from an international perspective, and its current performance globally and in South Africa, is provided. Chapter 2 concludes with a comprehensive discussion of the mobile app industry, including a general overview of this industry, and more specifically same-day delivery apps, as well as its current performance globally and locally.

2.2 THE SOUTH AFRICAN RETAIL LANDSCAPE

South Africa, a dynamic country with approximately 60 million diverse individuals, 12 official languages and an annual GDP of US$419 billion (Global Convenience Store Focus, 2021: 2), boasts diversity in terms of different cultures and ethnic and religious groups in addition to broad income clusters (Lappeman, Egan, Rightford & Ramogase, 2021: 89). The diverse nation differs immensely in terms of needs and expectations, along with unique political and socio-economic forces, which have ultimately shaped a complex and miscellaneous retail landscape (Lappeman

et al., 2021: 89). South Africa's retail market is one of the largest on the African continent, supporting a thriving retail market and continuing to experience mainly mall-based retailing (Global Convenience Store Focus, 2021: 2). Since the recession in 2009, the retail sector has grown, creating numerous employment opportunities each year (Teuteberg, 2020: 14). During the third quarter of 2019, the South African retail industry employed over 3.4 million South Africans (Teuteberg, 2020: 14) and is increasingly becoming consumer-driven, in addition to constantly adopting and benchmarking its offerings to meet international standards and trends (Van Niekerk, 2020: 55).

Despite the dominance of large retail groups, South Africa offers a myriad of small and medium businesses, with a large portion comprising mainly informal traders (Global Convenience Store Focus, 2021: 2). The South African retail industry spans from modern formal retailers such as Woolworths, Checkers and Pick n Pay, mostly serving the upper- and middle-income markets, to big-box cash-and-carry and hybrid stores such as Kit Kat Cash & Carry, convenience stores such as SPAR, as well as numerous informal retail stores (or spaza shops) selling mostly staple products in townships and to poorer communities. Both formal and informal retail businesses serving a diverse range of South African consumers play an integral role in the South African economy (Lappeman et al., 2021: 89).

The various retail sectors that represent the South African retail industry will be discussed further in the following section to demonstrate how the different retail sectors and formats serve the country's diverse demographic spread. First, though, retailing and retailers are placed within the context of the overall retail supply chain.

2.2.1 CONTEXTUALISING RETAILING AND RETAILERS

The retail supply chain is the series of businesses and exchanges required to get products from the manufacturer or producer to the end consumer. Members of the retail supply chain are collectively referred to as marketing intermediaries, which include various role players, such as manufacturers or producers, agents or brokers, wholesalers and retailers (Padgett & Loos, 2022: 171). A manufacturer is a person or business that produces finished products from raw materials by using various tools, equipment and processes, and then sells the products to consumers, wholesalers, retailers or other manufacturers to produce more complex products (Corporate Finance Institute, 2021). An agent or broker acts as a sales intermediary between the manufacturer and retailer and arranges, executes and facilitates client transactions (Unisa, 2017: 109). Wholesalers are intermediaries whose primary function is to acquire products from

manufacturers in large quantities and then distribute those products to various retailers, or occasionally, other wholesalers (Padget & Loos, 2022: 172). Retailers are intermediaries that purchase products from manufacturers or wholesalers and then resell the merchandise to the end consumer (Padget & Loos, 2022: 172). Retailing thus entails the activities of selling products to the general public in relatively small quantities for household use or consumption, rather than for resale (Lappeman et al., 2021: 87; Topps & Taylor, 2018: 6).

Different supply chains, or distribution channels, are found in the retail industry that supply products through the various stages between the manufacturer and the end consumer (Unisa, 2017: 107). Retailers make use of either a direct distribution channel, where products are distributed directly from the manufacturer to the end consumer, or an indirect distribution channel, where products pass through intermediaries (either one or many) before reaching the final consumer (Hatten, 2016: 318).

Several retail formats operate in the South African market as shown in Figure 2.1. The most notable include (1) department stores that sell a wide variety of manufacturers' products, such as Makro, (2) grocery stores that sell mainly food and beverages, but also occasionally homeware and home appliances, for instance Checkers Hypermarket, (3) Internet or online retailers who do not have a physical brick-and-mortar presence, but instead sell products through online portals, such as Takealot.com and Superbalist.com (e-commerce) and lastly (4) mobile retailers that make use of smartphone applications (apps) to sell products to consumers, for instance Woolies Dash and Uber Eats (m-commerce) (Van Niekerk, 2020: 53).

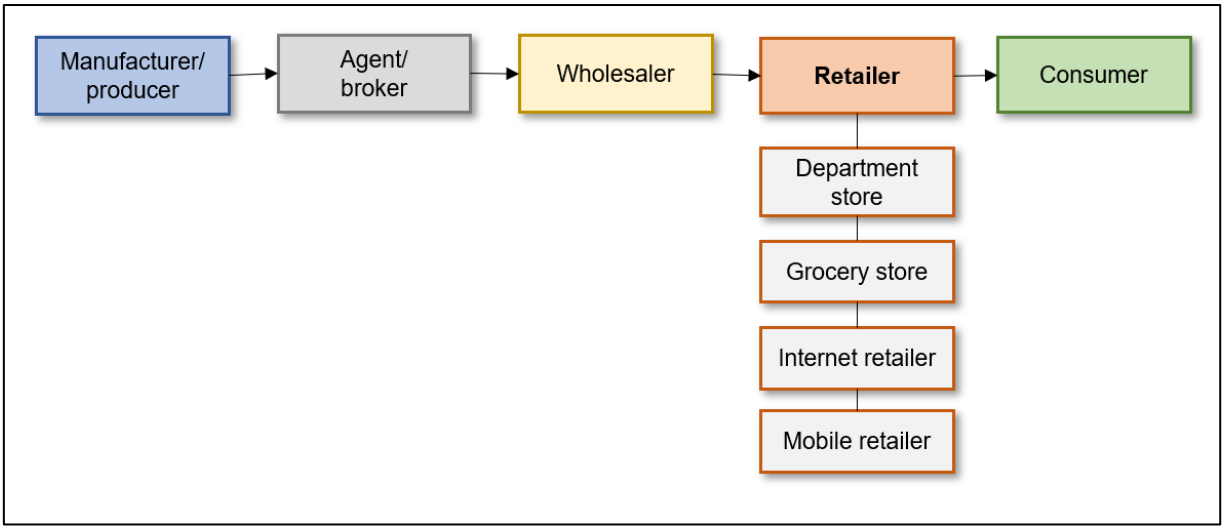

Figure 2.1: The South African retail formats within the retail supply chain

Source: Adapted from Van Niekerk (2020: 51)

Retailing is a vital part of any economy and ultimately links the end consumer with the manufacturer of various products. Daily, millions of South African consumers visit retail stores, whether brick-and-mortar stores or online retailers using the Internet or mobile data networks. The South African retailing industry is diverse and complex, with a wide range of retailers operating in each of the aforementioned retail formats. Although mobile retailing is of particular interest to the research study, the major retail sectors of South Africa are briefly discussed to understand the dynamics of the South African retailing industry, and better understand how these retailers were established.

2.2.2 THE SOUTH AFRICAN RETAIL SECTORS

As previously stated, South Africa is home to one of Africa's most sophisticated retail markets with a wide variety of retail formats and distribution channels to reflect the diversity of the country itself (Oxford Business Group, 2014: 112). The diversity of the country, along with unique political and socio-economic forces, has created a retail landscape ranging from contemporary formal retailers serving the upper-income market to thousands of informal retailers serving rural communities (Lappeman et al., 2021: 89). The combination of formal and informal retail businesses plays a vital role in the South African economy.

The sections to follow firstly deal with the formal and informal retail sectors of South Africa to offer a better understanding of how these retailers were established, their contribution to the overall retail industry and gross domestic product (GDP) and how each sector serves the demographically diversified South African consumer landscape. Secondly, a brief overview of the online retail sector will be given to lay the foundation for the remainder of the chapter, as the online retailing sector is the focal point of the research study.

2.2.2.1 Formal retailers

South Africa has the most developed formal retail sector in sub-Saharan Africa, owing to its well-developed infrastructure and relatively stable policies (Mwamba & Qutieshat, 2021: 1567). To be considered a formal retailer, a business must operate within South Africa's legal framework, be registered with the South African Revenue Service (SARS) and pay the applicable taxes on all generated income (Lappeman et al., 2021: 90).

According to Lappeman et al. (2021: 90), the formal South African retailing industry contains a variety of retail business ownership structures, from large corporate companies listed on the

Johannesburg Stock Exchange (JSE), such as Pick n Pay Stores Ltd and Shoprite Holdings Ltd, to voluntary buying organisations and small independent supermarkets operated by sole proprietors. Franchises and voluntary buying groups can be either corporate listed businesses, such as SPAR, or independent privately owned companies, for example Unitrade Management Services (Pty) Ltd (Lappeman et al., 2021: 90). Examples of the various business ownership structures found within the formal retailing sector are shown in Figure 2.2.

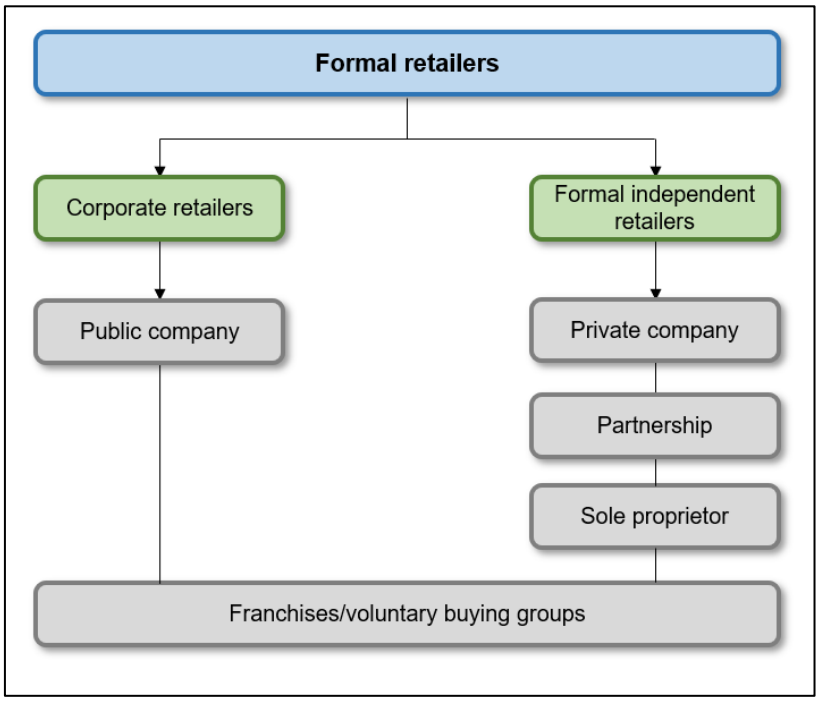

Figure 2.2: Forms of retail business ownership
Source: Adapted from Lappeman et al. (2021: 90)

The following discussion focuses on the two broad groups of formal retailers that can be found in the South African retailing sector: corporate retailers and independent merchants. These categories are discussed to better comprehend the diversity of the retailing landscape and how the various retail formats available in the South African market have modified their business models to include more advanced offerings, such as online and mobile shopping.

2.2.2.1.1 Corporate retailers

The formal corporate retail sector, also known as 'modern trade', due to the urbane fittings and fixtures of its stores, consists of public companies listed on the JSE (Lappeman et al., 2021: 92). Corporate retailing is dominated mainly by Shoprite Holdings Ltd, Pick n Pay Stores Ltd, Massmart Holdings Ltd (51% Walmart owned), The SPAR Group Ltd and Woolworths Holdings Ltd

(Lappeman et al., 2021: 93). Retail giant Shoprite Holdings Ltd alone has a presence in 14 other African countries, and 75% of its turnover is generated in South Africa (Mwamba & Qutieshat, 2021: 1567; Teuteberg, 2020: 14). Shoprite Holdings Ltd generated over R156 billion in revenue in 2020, followed by SPAR (R124 billion) and Pick n Pay Stores Ltd (R89 billion) (Teuteberg, 2021: 5).

In response to South Africa's high levels of income inequality, formal retailers have adapted with relevant formats and ranges to meet the needs of a consumer base extending from very poor to extremely wealthy (Lappeman et al., 2021: 93). As shown in Figure 2.3, retailers such as Woolworths, SPAR, Pick n Pay and Checkers serve the higher income cluster with stores that compete with exceptional quality products and excellent customer service. Discounters and no-frill supermarkets such as Boxer, USave and Shoprite bring lower-income consumers quality food at more affordable prices (Lappeman et al., 2021: 93).

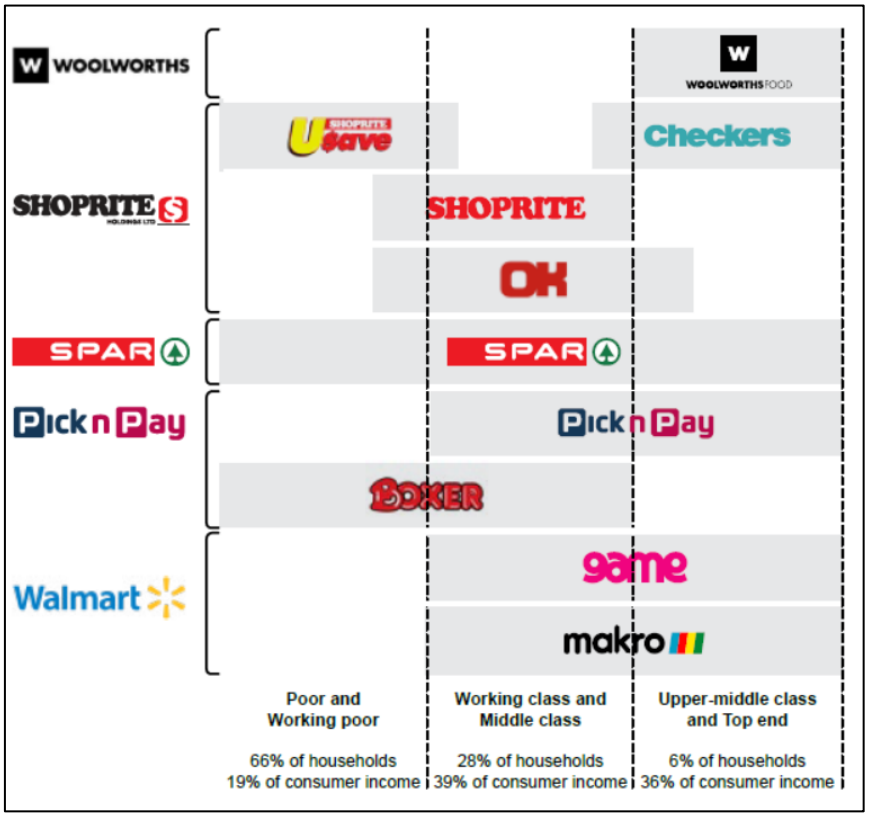

Figure 2.3: South African corporate retailers and the profile of their shoppers[2]
Source: Lappeman et al. (2021: 93)

[2] The profile of consumers was segmented according to the National Income Dynamics Survey (NIDS) data.

Formal retail entities are largely found in shopping centres across the country. A shopping centre is defined by Lappeman et al. (2021: 95) as "… a group of retail and other commercial establishments that is planned, developed, owned and managed as a single property, with on-site parking provided". South Africa is home to over 2 000 shopping centres spanning around 23 million m^2 of formal retail space – the sixth largest worldwide (Van Niekerk, 2020: 55). South Africa boasts a variety of different shopping centres, ranging from massive regional shopping centres such as Gateway in KwaZulu-Natal and Menlyn Mall in Gauteng, to relatively small neighbourhood shopping centres, such as Cosmos Mall in Randburg, and local convenience centres such as Parktown Quarters in Johannesburg.

The development of shopping centres during the late 1990s in poorer rural communities, such as the Maponya Mall in the Sowetan township, accelerated the expansion of the retailing landscape and offered corporate retailers access to unserved areas that were considered the domain of informal and independent retailers (Lappeman et al., 2021: 95).

2.2.2.1.2 Independent retailers

Formal retailers can also be classified as independent retailers. These retail businesses range from sole proprietors owning and managing a single store to private companies owning a chain of stores (Lappeman et al., 2021: 94).

Independent retailers are characterised by strong regional independent chain stores, such as Chamberlains or Checkout, and small businesses operating independently or as members of a franchise, buying group or voluntary trading organisation (Lappeman et al., 2021: 94). Figure 2.4 shows how some of the most significant independent retailers in South Africa use their brands to appeal to a variety of South African consumers.

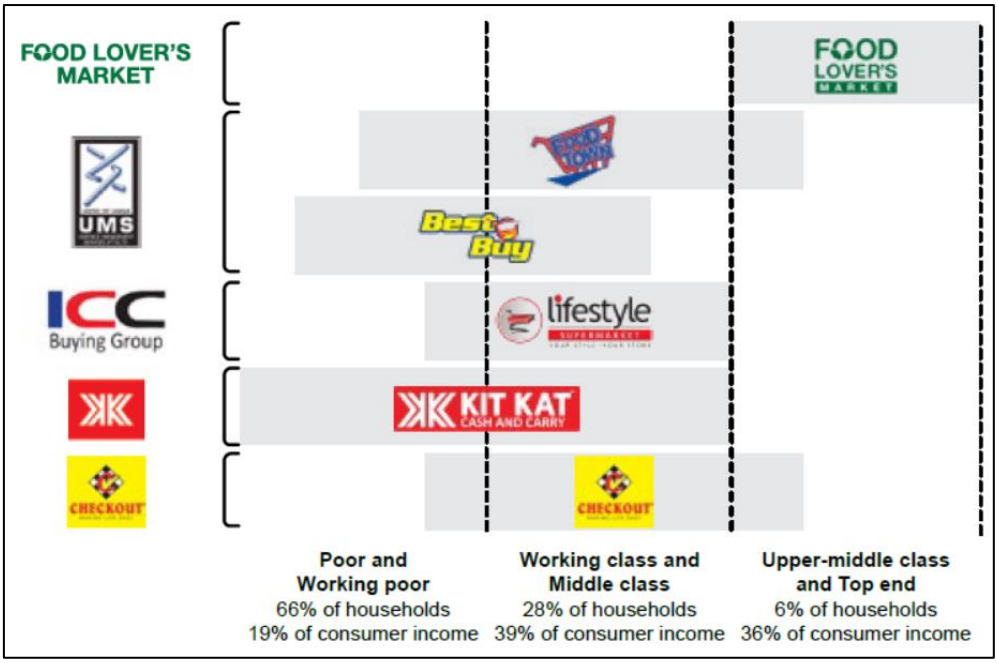

Figure 2.4: Formal independent retailers and the profile of their shoppers
Source: Adapted from Lappeman et al. (2021: 94)

Although buying groups and voluntary trading organisations play a crucial role in the retailing sector, businesses such as Unitrade Management Services (UMS), the Independent Cash-and-Carry (ICC) Buying Group and the Independent Buying Consortium (IBC), are largely unknown entities to the general public due to their brands bearing no resemblance to their corporate retail brands (Lappeman et al., 2021: 94).

It is believed that the vast development and extension of shopping centres into poorer communities negatively impacted independent and informal retailers. With shopping centre developers favouring corporate retailers, it created barriers to entry for strong regional independent retailers and significantly impacted South Africa's informal retailer sector. The next section deals with the informal retail industry of South Africa.

2.2.2.2 Informal retailers

Informal retailers essentially consist of "… small, unregistered businesses operating as street vendors and in-home businesses established on residential sites", often termed spaza shops or tuck shops in South Africa (Lappeman et al., 2021: 90). The informal retail sector generally lacks formality in terms of business licences, VAT registration, operating permits and accounting procedures (Odendaal, 2014). The informal retail sector, as suggested by Trade Intelligence (2020), is worth R158 billion.

The informal retail sector plays a vital role in the South African economy and contributes largely to employment, food security, income generation and business development in the poorer communities (Lappeman et al., 2021: 90). Its emergence, according to Ligthelm (2005: 199), is due to the divergence between the growth in the urban population and employment growth in the formal economy. Informal retailers are the backbone of township economies, but the lack of credit and constant competition with modern corporate retailers are challenges these retailers face daily (Nieuwoudt, 2020).

Although informal retail ranges from hawkers and table-top operators to informal chemists, shebeens, fixed structure stores and small supermarkets, the majority of the informal market is made up of spaza shops and spazarettes (Lappeman et al., 2021: 96). When trading restrictions on black people were implemented during the apartheid era, these people began to hide their stores from authorities by operating out of roadside shacks or residential properties; hence the name *spazas*, which means 'hidden' (Lappeman et al., 2021: 96). The literature suggests that there are approximately 150 000 spaza shops or small informal businesses operating in South Africa (Nieuwoudt, 2020) which employ more than 2.6 million people and contribute about 5.2% to South Africa's GDP, while supporting 35% of total grocery sales in South Africa (Adam, 2020).

Spazarette stores, on the other hand, are small supermarket-styled stores with aisles and a larger range of merchandise. Spazarettes furthermore have a wholesale section, offering bulk products to hawkers and local food outlets selling street food, such as *kotas*, *amaplati* and *vetkoek* (Alcock, 2020: 13). There are about 30 000 spazarettes in South Africa, and research has shown that these spazarettes are on average 5% to 10% cheaper than formal retailers on a basket of branded groceries (Alcock, 2020: 13). It is estimated that 70% to 80% of all spazarettes are operated by immigrants, the majority of whom are from Somalia, Bangladesh, Pakistan and Ethiopia (Lappeman et al., 2021: 97).

Informal retail businesses are categorised as either survivalists or networked informal retailers. South African informal retailers have emerged from a long background of enduring survival in oppressive circumstances. For many years they were considered illegal and are confined to legal uncertainties on land use and zoning (Sustainable Livelihoods Foundation, 2015: 4). Historically, informal retailers, such as spaza shops, had low barriers to entry, thus allowing women and the unemployed to operate a small shop in their homes to make a modest living (Sustainable Livelihoods Foundation, 2015: 5). The survivalist category therefore refers to micro-enterprises, particularly spaza shops, which are run by a sole proprietor and for which the shop provides a minimum livelihood for the business owner and their family (Competition Commission, 2019: 20;

Lappeman et al., 2021: 97). Networked informal businesses, on the other hand, include informal retailers belonging to a broader trade community network that facilitates more effective trading.

With an increase in disposable income and a growing population, informal settlements have become an attractive market for corporate retailers. Shoprite Holdings Ltd has fast-tracked the launch of its USave eKasi container stores in townships, which range from 100 m^2 to 200 m^2 stores. Its competitor, Pick n Pay, has also collaborated with independent traders and has started upgrading existing spaza shops. The South African start-up community is rapidly transforming the way informal retailers do business and access credit. Businesses are connecting informal traders to suppliers and customers and making it easier for informal traders to manufacture and sell products and manage their own businesses (Nieuwoudt, 2020).

The retail sector is changing rapidly worldwide, particularly due to the onset of the worldwide COVID-19 pandemic, which resulted in an unprecedented increase in the adoption of online retailing. Online retailing has allowed many retailers to broaden their target area and serve previously unreached markets (Mwamba & Qutieshat, 2021: 1567). Online retailers span both formal and informal retail operations (Lappeman et al., 2021: 89) and will briefly be discussed in the next section.

2.2.2.3 Online retailing (e-tailing)

Online retailing, also referred to as electronic retailing or e-tailing, is considered an element of the wider e-commerce industry (Teuteberg, 2020: 14). E-tailing entails the sale of products and services through an electronic medium, such as the Internet (Investopedia, 2021; Van Niekerk, 2020: 62). E-tailers generally include brick-and-click stores, which are traditional retailers that have adopted elements of online retailing, and pure-play stores, which only exist online and do not have a physical store (Warf, 2018: 351).

With the rise of e-commerce (discussed in section 2.3 below), businesses had to adapt their business models to capture Internet sales, which included expanding distribution channels such as warehouses, Internet webpages and product shipping centres (Investopedia, 2021). Successful e-tailing requires strong branding, a durable distribution network that is quick and effective, an engaging website that is easily navigable, competitive prices and customer value, and regular updates to meet consumers' changing needs (Investopedia, 2021).

To understand where mobile shopping apps and specifically same-day delivery apps derived from, the rise and evolution of the e-commerce industry and how e-tailing forms part of this broader industry will be discussed.

2.3 EVOLUTION OF E-COMMERCE

The term ‘online shopping’, often referred to as electronic commerce or e-commerce, is described as the wide range of commercial transactions conducted online with the exchange of money or data (Maiti & Sadhukhan, 2020: 2). More comprehensively, Maiti and Sadhukhan (2020: 2) describe e-commerce as “… the platform to create, transform or redefine relationships for value creation among or between organisations and between individual and organisation by the use of electronic communications and digital information processing technology”. E-commerce takes place through a range of different commercial relationships, including business-to-business (B2B), business-to-government (B2G) and increasingly more business-to-consumer (B2C) transactions (OECD, 2019: 14). E-commerce includes e-tailing, e-banking, e-shopping, e-logistics, e-marketing and advertisement, e-bookings, e-stock trading, e-publications and e-medical services (Maiti & Sadhukhan, 2020: 2).

E-commerce has fundamentally changed the process of buying and selling products, and its continued expansion is changing the nature of retailing globally, influencing product availability, inventory, transportation, pricing structures and consumer behaviour (Lappeman et al., 2021: 99).

In the next section, the growth and development of e-commerce, globally and in South Africa, are discussed in more depth.

2.3.1 THE RISE AND EVOLUTION OF E-COMMERCE: A GLOBAL PERSPECTIVE

E-commerce is claimed to have originated in the United States of America (USA) in 1969 when CompuServe became the first company to offer users of personal computers access to electronic mail and technical support (CompuServe, 2021). In 1979, inventor Michael Aldrich created an online shopping system called Videotex, to enable online transactions between consumers and businesses or other parties. To do this, Aldrich modified a television and used a telephone line to connect it to a multi-user transaction processing computer, one of the first end-user technologies that displayed interactive information on a television screen (Dragan, 2013; Harbone, 2019). However, the first formal online order was only placed by an elderly woman in 1984 while using a remote, television and Videotex (Van Niekerk, 2020: 62). Boston Computer Exchange (BCE), the

world's first e-commerce company, launched the first e-commerce platform in 1982, using online databases to allow users and sellers to buy and sell computers and computer parts online (Harbone, 2019). BCE were in operation before the Internet was commercialised and made readily accessible to the general public in 1991 (Van Niekerk, 2020: 62).

The rise of the Internet in the 1990s and the introduction of the World Wide Web in 1991 fuelled the growth of e-commerce as many companies expanded their business model to the Internet (Maday, 2020; OECD, 2019: 13; Zwass, 2019). Congruently, the revolution of online retailing was born during the expansion of the 'dotcom' era in the late 1990s and early 2000s (Warf, 2018: 351). During the growth of the Internet and the World Wide Web, online retailing was predicted to rise by 75% annually. Investors rapidly capitalised on the ostensibly radical development in online shopping but quickly failed due to exorbitant start-up costs, a lack of infrastructure required to deliver products directly to customers and failure to attract enough customers to sustain the new business model.

One of the first successful online retailers, Amazon.com launched in 1995, has grown to a company valued at US$45.7 billion, making it the largest e-retailer in the USA (Warf, 2018: 351). Amazon, founded by Jeff Bezos, started as a small online bookstore in Seattle (DePillis & Sherman, 2018) and has since then revolutionised the e-commerce industry (Maiti & Sadhukhan, 2020: 3). Amazon has grown to being not only the foremost online shopping retailer globally, but also the leading retailer selling a wide range of products, including books, clothing, fragrances, appliances and technology, among other things (Van Niekerk, 2020: 62). Moreover, the internationally acclaimed e-commerce company, eBay, founded in 1994 by Pierre Omidyar, offered a website dedicated to bringing together buyers and sellers in an open marketplace (eBay, 2021). As of September 2021, eBay had a net worth of US$49.75 billion (Macro Trends, 2021). In China, Alibaba was launched in 1999 as a business-to-business (B2B) e-commerce site and since then has expanded its ventures to include a business-to-consumer (B2C) site and a consumer-to-consumer (C2C) online marketplace. After the rise of Amazon, eBay and Alibaba, e-commerce rapidly expanded as many companies invested in online commerce.

Online sales growth has in many international markets surpassed physical store growth. Owing to the availability and expansion of digital retailing, consumers can purchase a wide range of products which may not be available in-store, online from their desktops or mobile devices, compare prices, check product availability and place orders from anywhere at any time (Fuentes & Svingstedt, 2017: 137). Following a major shift to online retailing in 2020, e-commerce sales are expected to grow throughout 2023 and account for a rising portion of all retail sales worldwide

(Lebow, 2021). Global e-commerce sales accounted for US$5.2 trillion in sales in 2022 (Pasquali, 2022), and are expected to reach US$6.17 trillion by 2023 and account for a 22.3% proportion of all retail sales, up from US$3.35 trillion and 13.8% in 2019 (Lebow, 2021), as shown in Figure 2.5.

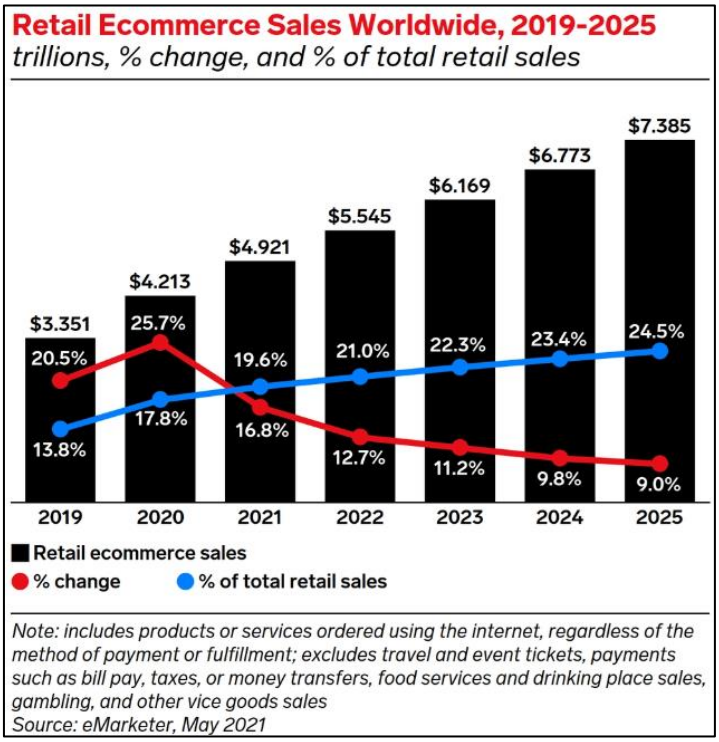

Figure 2.5: Retail e-commerce sales worldwide (2019 – 2025)
Source: Lebow (2021)

Despite the wide-reaching difficult year experienced by the retail industry due to the worldwide COVID-19 pandemic, retail e-commerce sales growth increased globally – a 27.6% increase in retail e-commerce sales was recorded in 2020 worldwide (Keenan, 2021). In May 2020, USA-based e-commerce retailer, Amazon, alone doubled their total online sales, and Mastercard revealed a 92.7% increase in e-commerce sales during the same period (Teuteberg, 2020: 3).

When compared to a global perspective, the evolution of e-commerce in developing countries such as South Africa is somewhat different. The following section covers South Africa's e-commerce sector as impacted by the COVID-19 global pandemic.

2.3.2 THE E-COMMERCE SECTOR OF SOUTH AFRICA

Two decades ago, the Internet was launched in South Africa, with the first '.co.za' domain being registered in June 1992. South Africans began purchasing products online in 2001, and by 2003,

the retail industry haf made R341 million in online sales (Van Niekerk, 2020: 63). The South African online retail sector generated R55 billion in 2022, nearly doubling the R30.2 billion in sales generated in 2020 (Hattingh & Ramlakan, 2022: 6). By the end of March 2021, more than 57.5% of the South African population was connected to the Internet (Kallier, 2022: 39). The South African e-commerce landscape, although small compared to developed international markets – the 40th largest market for e-commerce (EcommerceDB, 2023) – has seen rapid growth in scope and value (Mofokeng, 2021: 1).

The expansion of e-commerce in South Africa was reportedly hindered by poor Internet quality, high data prices and poor infrastructure (Goga et al., 2019: 2; Mwamba & Qutieshat, 2021: 1567). Two factors are mentioned by Lappeman et al. (2021: 99) that hampered the growth of online retailing in South Africa. Firstly, of a population of about 60 million citizens, 36 million belong to households earning an income of R8 000 or less per month. Consequently, expensive data costs and access to Internet service providers create an access divide across the population. Of the 28 million citizens who have access to the Internet, 21 million access the Internet via a mobile device, whereas a mere 3.5 million of these individuals engage in online shopping. Secondly, online retail growth will accelerate when data costs decrease, delivery logistics improve and the trust in online retailers increases among customers (Lappeman et al., 2021: 99). At present, however, consumers are gradually spending more on their mobile phones as a result of expanding mobile penetration in the country and the availability of more affordable smartphones in the South African market, such as Huawei, Xiaomi and Hisense (Van Niekerk, 2020: 65).

In 2020, e-commerce witnessed a substantial increase in the demand for home deliveries due to COVID-19-induced lockdowns and a decline in brick-and-mortar retail sales (Daniel, 2021; Deloitte, 2021: 5). The global developments in e-commerce and m-commerce, particularly the growing reliance on online or mobile commerce, were hastened by the coronavirus disease (or COVID-19), which was originally discovered in the city of Wuhan in China during December 2019 and quickly spread throughout the world (Teuteberg, 2020: 3).

In South Africa, the retail industry was heavily impacted when the country went into strict lockdown on 26 March 2020 due to the COVID-19 pandemic. Curfew restrictions prevented residents from leaving their homes except to buy necessities such as food and medicine (Global Convenience Store Focus, 2021: 3). The demand for home deliveries escalated by 66% as a result of the COVID-19 pandemic, increasing South Africa's total online retail sales from R14.1 billion generated in 2018 to R30.2 billion in 2020 (Daniel, 2021; Deloitte, 2021: 4; World Wide Worx, 2021b). While many sectors were negatively affected by the lockdown enforced in 2020, online

retailers experienced an increase in sales as South Africans avoided shopping malls and stores in lieu of home deliveries. The losses incurred by traditional retailers with consecutive lows recorded during 2020 correlate with the gains made by online retailers, which doubled their combined market share to 2.8%. During the pandemic, popular South African e-tailer, Takealot.com, grew its revenue by 41% to more than R3.3 billion (Daniel, 2021). While the e-commerce industry is expected to continue its rising trajectory, reaching R42 billion sales in 2021 and increasing its total market share to approximately 4%, the COVID-19-induced success is unlikely to be repeated.

M-commerce is rapidly outpacing its desktop and brick-and-mortar equivalents (Bhavsar, 2018). The number of smartphone subscribers globally surpassed 6.3 billion users and is forecasted to further grow to approximately 7.5 billion users by 2026. Just over 90% of the world's population is projected to use a smartphone by 2026 (Statista, 2021e). As the smartphone penetration rate is still below 70% in many densely populated nations, especially China, the smartphone market has significant potential for development. The countries with the most smartphone users are China (912 million), India (439 million), the USA (270 million) and Indonesia (160 million), most likely due to the size of the population (Statista, 2021c). In comparison to these figures, approximately 20 to 22 million South Africans, or about 36% of the country's population, use smartphones. However, with more than 90 million mobile network subscribers, the total number of mobile connections is substantially higher, indicating that many people possess multiple mobile devices (Statista, 2021e). More than half (60.7%) of South Africans used mobile devices to access the Internet in 2021 (Kallier, 2022: 7). Furthermore, South African consumers rely heavily on mobile devices to engage in m-commerce and e-commerce activities, spending about 5 hours per day using the Internet via mobile devices, compared to the global average of 4 hours per day (Ngubelanga & Duffett, 2021: 2).

Evident from the above statistics is that increasingly more individuals have access to a smart device with Internet connectivity. The abovementioned statistics alone are the main reason for the shift towards m-commerce. However, a variety of environmental circumstances and lifestyle preferences have had an impact on consumers' shopping needs and behaviours, shifting them to a world where mobile devices dominate. Mobile devices' portability and time effectiveness enable customers to purchase goods and/or services anywhere at any time (Bhavsar, 2018). The reliability of high-speed Internet connections and the availability of several mobile apps provide more digital touch points for retailers to connect with customers (Bhavsar, 2018).

Due to changes in consumer behaviour, businesses must now embrace a 'mobile first' business strategy, and mobile platforms cannot be ignored any longer. It is noticeable that retailers that embrace m-commerce have a competitive edge and continue to experience significant traction from customers (Bhavsar, 2018). An increasing number of retailers have changed their business models to incorporate m-commerce opportunities, enabling them to access a wider market through a variety of channels. As a result, in today's 'always on' technological era, retailers must constantly adapt to the needs and demands of customers to maintain a competitive advantage and reach a wider audience.

The m-commerce and mobile app industry is discussed in the subsequent section.

2.4 M-COMMERCE AND THE MOBILE APP INDUSTRY

Mobile shopping, also known as mobile commerce (or m-commerce), is a subset of e-commerce that has been defined in many ways. M-commerce is described as a form of e-commerce using a wireless handheld device such as a smartphone (Bloomenthal, 2020). The definitions of Gupta and Arora (2017: 2) and Farhaoui (2020: 248) are closely aligned, stating that m-commerce comprises applications and services that are accessible from the use of wireless Internet services and Web-enabled mobile devices. Pahwa (2018) and Sandhu (2012: 759), on the other hand, explain m-commerce as "… any transaction involving the transfer of ownership or rights to use goods and services, which is initiated, facilitated and/or completed by the use of [a] mobile or handheld device and wireless technology". More recently, however, the scope of m-commerce has begun to transform to include a wider range of activities (Van Niekerk, 2020: 64). M-commerce, according to Fuentes and Svingstedt (2017: 137), involves the use of a mobile device to make a purchase, including using the device to check and compare products and prices, gather relevant information relating to a product of interest and reading reviews from customers who have previously purchased the same product. For the purpose of the research study, Fuentes and Svingstedt's conceptualisation of m-commerce (2017: 137) is used as their definition includes an all-encompassing overview of the functions provided using a wireless handheld device, such as a smartphone. M-commerce is considered an extension of e-commerce since it modernises online business by expanding it to new application areas and a new target market with appropriate economic models and pricing structures (Farhaoui, 2020: 248). M-commerce offers users many additional benefits, including personalisation, identification and localisation (Van Niekerk, 2020: 3).

M-commerce emerged as a result of developments in wireless telecommunications, which were first designed to carry voice transmissions between individuals and businesses (Tan & Teo, 2001). The term 'mobile commerce' was first coined by Kevin Duffey in 1997 at the launch of the Global Mobile Commerce Forum and was described as "… the delivery of electronic commerce capabilities directly into the consumer's hand, anywhere, via wireless technology" (Global Mobile Commerce Forum, 1997). M-commerce was brought to life later the same year by Coca-Cola, which installed two mobile phone-enabled vending machines in Helsinki, Finland, that accepted payments via SMS text messages. Shortly thereafter, the first mobile phone banking service was launched by the Merita Bank of Finland. The concept was further validated in 1998 when the first commercial sale of digital content, such as ringtones, on mobile devices became possible. Since then, various m-commerce activities emerged, such as mobile-facilitated payments and transactions relating to parking, train ticketing, airline ticketing, mobile contests and voting for favourite reality show contestants.

The iPhone's introduction by Apple Inc. in 2007, however, marked a significant advancement in m-commerce, moving it from SMS messaging to real mobile applications. Smartphones, such as the IOS and Android operating systems, made m-commerce possible as it is known today (Pahwa, 2018). Mobile devices are currently used to access a variety of goods and services, such as mobile banking, brokerage and money transfers; mobile ticketing; mobile vouchers, coupons and loyalty cards; content purchases and delivery; location-based services; information services; auctions; mobile purchases; in-app purchases and payments; and mobile marketing and advertising.

Over the years, the online share of traffic has shifted away from desktop purchases. In January 2020, mobile traffic made up 52% of all web traffic, and desktop traffic made up 45.3%, compared to the 48% each accounted for in February 2019. Additionally, with approximately 5.2 billion mobile phone users in the world, 40% exclusively use their smartphones for searching (Petrov, 2023). The high amount of mobility offered by contemporary phones is what has caused the recent development. As long as customers have access to the Internet and their smartphones, customers may purchase from anywhere in the world. Globally, m-commerce sales contributed US$3.56 trillion in sales in 2021 – 22.3% more than the US$2.91 trillion recorded in 2020 (Oberlo, 2021; Samsukha, 2023). The market share of m-commerce has increased significantly from 52.4% in 2016. M-commerce accounted for 72.9% of all e-commerce sales globally in 2021 (Petrov, 2023). It is projected that the global m-commerce market will reach US$5.7 trillion by 2026, growing at a compound annual growth rate of 19.8% (Ali, 2021).

From a South African perspective, nearly a third (36%) of the population, or between 20 and 22 million people, use smartphones. However, the total number of mobile connections is far higher, demonstrating that many South Africans have numerous mobile devices, with more than 90 million network subscribers (Statista, 2021e). Due to the country's rising mobile penetration, customers are spending more time and money on their smartphones (Van Niekerk, 2020: 64). As previously mentioned, the increased penetration is believed to be due to the introduction of more affordable smartphones into the South African market, such as those from Huawei, Hisense and Xiaomi (Van Niekerk, 2020: 64). South African consumers spend about 5 hours per day using the Internet via a mobile device, compared to the global average of 4 hours per day (Ngubelanga & Duffett, 2021: 2).

Despite the growth of m-commerce globally, brick-and-mortar stores still dominate the South African retailing landscape (Monzon, 2022). Musakwa (2021: 16) reports that 63% of South African consumers preferred to purchase in-store in 2019, with just 1% to 2% of all retail spending occurring online in 2017. Furthermore, only 1.4% of total retail sales were made through a digital medium such as an online or mobile store (Van Niekerk, 2020: 65). Compared to tablets and mobile devices, desktop computers and laptops still account for a significant majority of digital purchases. The high slant towards the use of desktop computers or laptops, average 84%, compared to tablets at 10% and mobile phones at 6%, shows that digital purchases are still disproportionately made on these platforms as opposed to tablets and other mobile devices (Van Niekerk, 2020: 65).

More recent research has, however, shown that online shopping is gradually starting to shift from desktops to mobile devices, with mobile shopping contributing 46% to the retail sector's revenue, compared to 25% from desktops and 9% from tablets (Bayhack, 2020). This trend could be attributed to the demand for more online shopping platforms and home deliveries due to COVID-19-induced lockdown restrictions and attempts to maintain social distancing (Daniel, 2021; Deloitte, 2021: 5).

Deloitte's digital commerce survey (2021: 6) reveals that consumers' purchasing journey has increasingly become a blend of in-store and online shopping experiences across all categories, as shown in Figure 2.6 below.

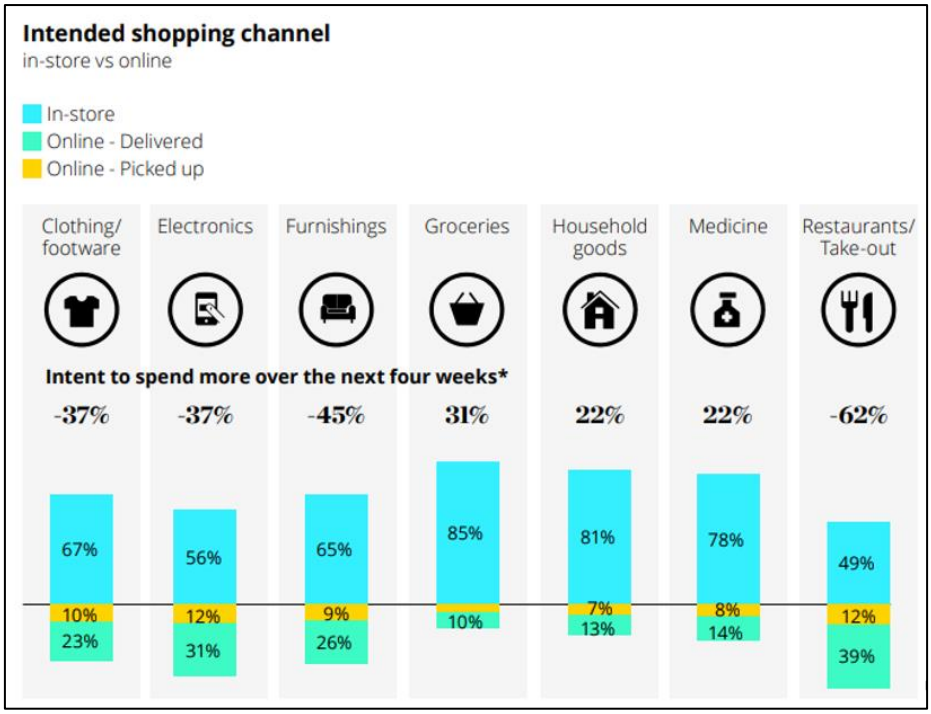

Figure 2.6: Intended shopping channels (in-store vs online), South Africa, 2021

Source: Deloitte (2021: 6)

Despite the fact that online and mobile shopping currently represents a relatively small portion of all retail sales, South Africa has taken notice of the growing opportunity these digital retailing channels bring. The exclusively online shopping market in South Africa is rapidly developing (Van Niekerk, 2020: 66). In November 2020, a study conducted by Mastercard revealed that 68% of respondents are shopping more online since the onset of the COVID-19 pandemic (World Wide Worx, 2021a). Approximately 22 million South African consumers shopped online during 2020, which is expected to increase by 44% to 32 million consumers by 2024 (Deloitte, 2021: 5). In their consumer insights report, Deloitte (2021: 6) found that more than 70% of survey respondents shopped online at least once a month, reporting that the reason for increased online shopping was that it was more convenient (26%), they shopped online due to the COVID-19 pandemic (25%), it saved time and had shorter waiting periods (23%) and it was the safest option (11%) (refer to Figure 2.7).

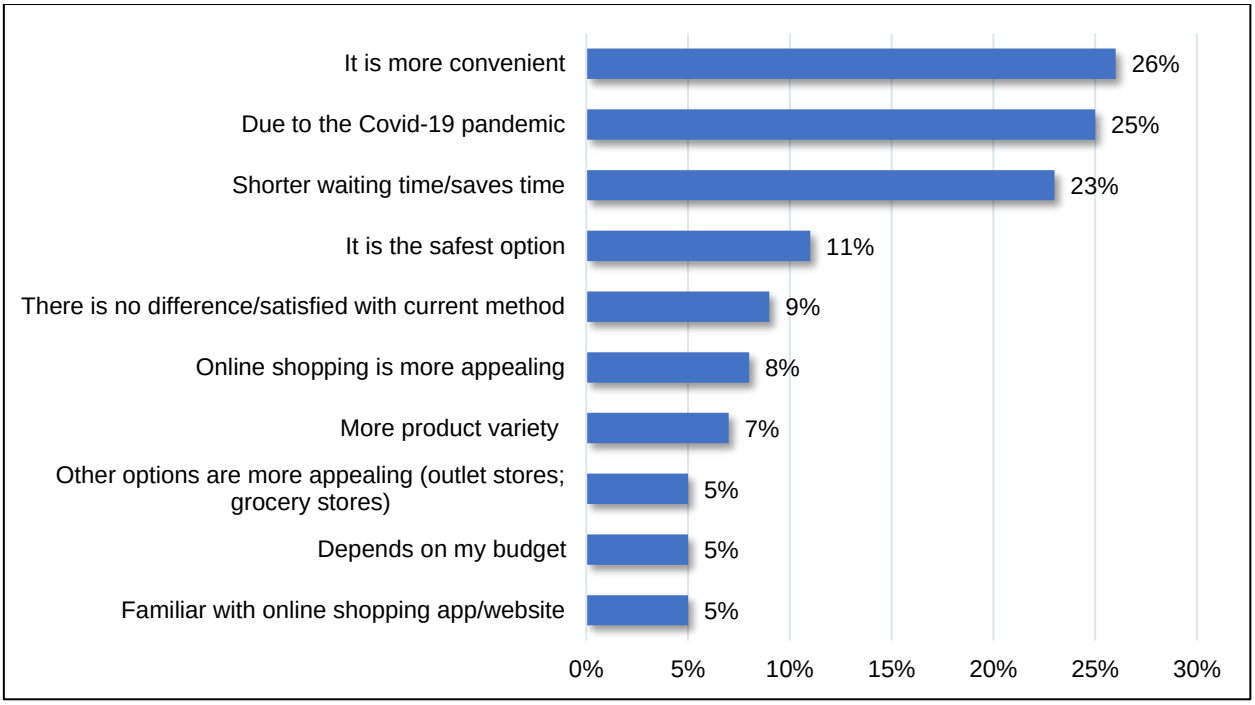

Figure 2.7: Reasons for increased online shopping in South Africa

Source: Deloitte (2021: 5)

South Africa has welcomed several new, solely online and mobile retailers over the past few years, including Takealot.com, Superbalist.com and Zando. Additionally, more established retailers, including Mr Price and Truworths, opened online stores in 2016, and some retailers also launched a mobile shopping app. Takealot.com is reportedly the industry leader with a market share of roughly 12.5%, outpacing Spree, which has been a part of Superbalist.com since 2018, by 1.4%. (Van Niekerk, 2020: 66). While online retailers, like Takealot.com and Superbalist.com, benefited from the change in consumer behaviour spurred on by the COVID-19 pandemic, offline retailers were forced to respond with the speedy rollout of new technologies, mobile apps and innovative ways of meeting consumers' needs, such as click-and-collect options (SpaceMatch, 2020).

The mobile app industry, with a specific emphasis on mobile shopping apps, will be discussed in the next section.

2.4.1 THE MOBILE APP INDUSTRY

A mobile application, or app, is a type of application software designed to run on a mobile device, such as a smartphone or tablet computer, and frequently serves to provide users with similar services to those accessible on a computer or laptop (Miladinovic & Xiang, 2016: 7; Pham, 2021).

Mobile apps, according to Ahn (2019: 2), provide users with information and services to achieve tasks and activities without the time and location restrictions.

When mobile apps were initially advocated by Apple Incorporated in 2007, the purpose of available mobile apps was to provide general services and information on the global network, such as e-mail, stock markets, listings, calendar and the weather. Typically referred to as native apps, these apps were developed primarily for a specific operating system, such as IOS or Android, and were pre-loaded as a default app on any smart device (Pham, 2021). The increased demand from mobile users, however, together with the improvements in mobile app technology and infrastructure, meant that mobile apps extended into many other categories, such as games, business, education, entertainment and lifestyle apps, to name but a few.

When Apple opened the first online App Store in 2008, only 800 apps were available for download, which considerably increased to approximately 4.8 million by the end of 2022 (Ceci, 2022). In addition, roughly 2.68 million mobile apps were available for download from the Google Play Store in 2022 (Ceci, 2022), followed by the Amazon Appstore offering just over 792 000 apps (42Matters, 2023). The Microsoft Store (previously known as the Windows Store) offered approximately 669 000 mobile apps in 2021 (Anthony, 2023). The mobile app industry has expanded rapidly since the launch of the first smartphone device app in 2008 and has led to the development of many different types of mobile apps (Merrick, 2016).

Mobile apps are divided into 20 broad categories, including utility, literature, business, education, entertainment, games and lifestyle, with several sub-categories. For example, lifestyle apps include fitness, travel, food and drink, dating and music apps (Buildfire, 2021; Merrick, 2016). The most popular mobile apps (i.e. the most downloaded apps), based on availability from the Apple App Store are games (21.49%), business-related apps (10.1%), educational apps (8.67%), lifestyle apps (8.61%), utility apps (6.25%) and entertainment apps (5.71%) (Statista, 2021b).

Figure 2.8 lists the most popular categories of apps available on the App Store.

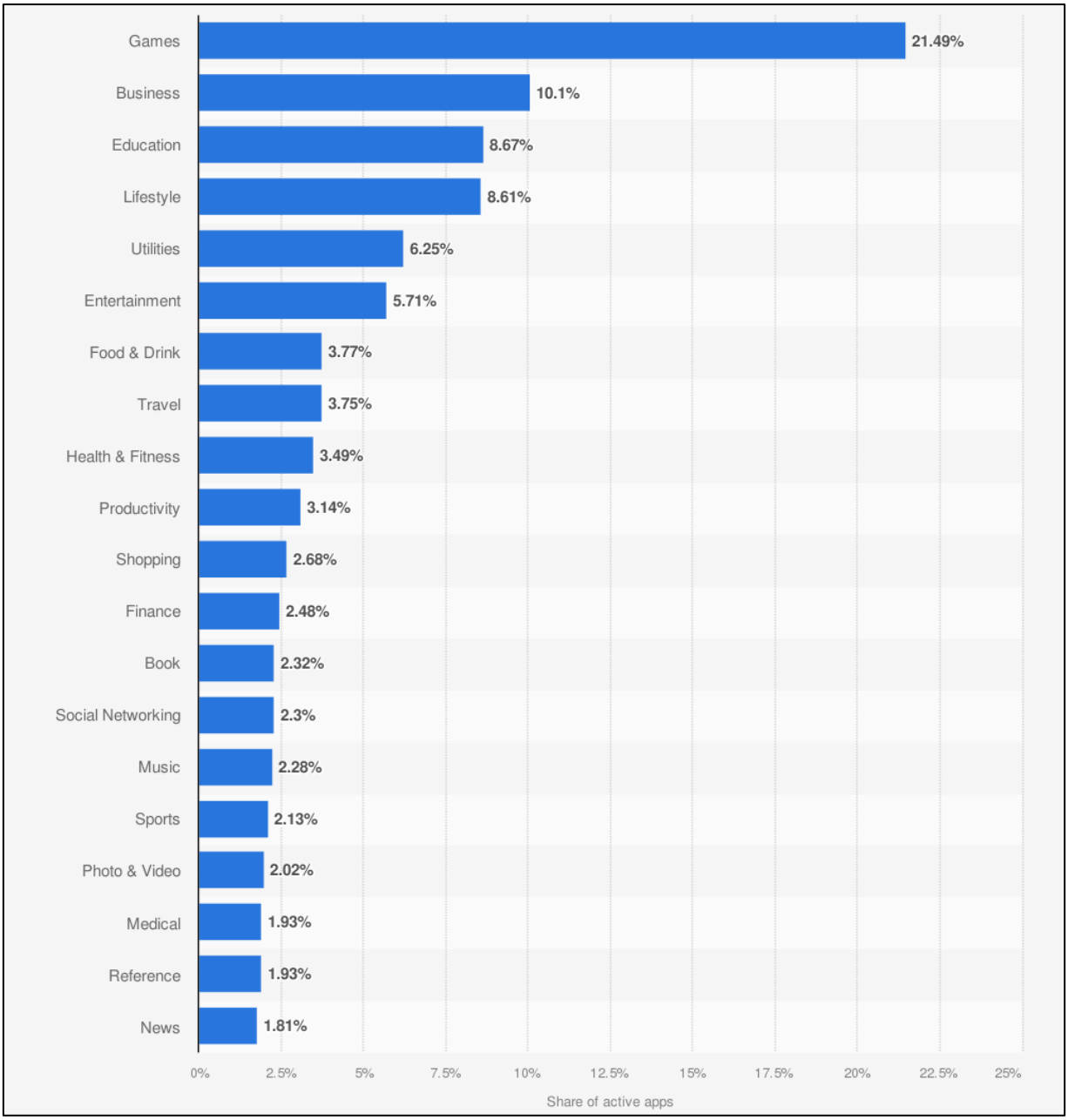

Figure 2.8: Most popular Apple App Store categories by share of available apps, June 2021
Source: Statista (2021b)

Smartphones have become an indispensable commodity of communication in modern society (Lee et al., 2019: 1). Since 2020, more than 5.2 billion individuals around the globe use mobile devices and it is estimated that nearly 97% of these individuals use a smartphone (Hootsuite, 2021: 20). The fast increase in smartphone penetration and high-speed network services have enabled businesses to deliver information to individuals more quickly and efficiently than before, allowing customers to use various information services beyond time and space constraints (Choi,

2020: 1). In South Africa, it is forecasted that mobile apps will generate US$71 million (R1.06 billion) by the end of 2024 (US$1 = R14,90) (Hootsuite, 2021).

Based on the above discussion, it is clear that customers' dependence on mobile devices to participate in e-commerce and m-commerce activities in South Africa has increased significantly, owing primarily to the COVID-19 pandemic (Ngubelanga & Duffett, 2021: 2). Individuals had to live in seclusion as the coronavirus spread over the globe. Nearly every element of daily life has shifted online, and individuals became more reliant on software applications, Internet connections and digital devices for socialising, working, learning, shopping and having fun (Kallier, 2022: 42). Despite the fact that lockdown restrictions were eased in June 2020, many of the behaviours adopted during the lockdown have persisted, increasing various digital activities.

Customers across the globe now have access to a world of possibilities owing to the availability of smartphones and, more specifically, mobile apps. As a result of the widespread use of mobile apps, which now include advanced personalised and interactive features, mobile apps have become an integral part of daily life (Musakwa, 2021: 14). Mobile apps have fundamentally expanded traditional shopping hours by allowing customers the means to purchase an array of products online 24/7 to be delivered almost anywhere (Van Niekerk, 2020: 3). With 64% of shoppers globally preferring to shop via mobile shopping apps (Van Niekerk, 2020: 4), businesses across all industries are developing these apps to create a more social and personalised shopping experience for customers (Wong, 2015).

With the increase in the number of smartphone users in the global marketplace – 5.2 billion users worldwide (Petrov, 2021) – m-commerce and mobile shopping have developed at an astonishing rate. Compared to the other mobile app categories shown in Figure 2.8 above, shopping apps are not very common among Apple users (2.68%), but their popularity has increased more than twofold since 2018 (101.5%) and is anticipated to rise yearly (Singh, 2020: 1). Among Android users worldwide, shopping apps had a market share of 35.8% (Statista, 2021a). Additionally, in the fourth quarter of 2020, shopping apps grew by 14.3%, followed by food and beverage apps (11% growth) and social networking apps (8.42% growth) (Anthony, 2023).

In 2012, a total of 210 million users worldwide had purchased retail goods via their mobile device, which increased to 1.09 billion users in 2018 (a 519% increase) (Statista, 2021f). By the end of 2023, it is anticipated that mobile sales will have produced over US$935 billion in revenue, up from US$330.4 billion generated in 2013 (Buildfire, 2021; StatInvestor, 2021). Newman, Wachter and White (2017: 1) claim that consumers devote nearly 25% of their overall app usage time

specifically to retailers' apps. The increase in smartphone users has led to a tremendous increase in the number of mobile apps that consumers use on their smartphones daily (Saifi, 2017).

While online and mobile shopping represents a small percentage of total retail sales in South Africa (R30.2 billion) (Deloitte, 2021: 4), the growth potential presented by these digital retailing channels is expanding at a rapid pace. Since 2011, many new and exclusive online and mobile retailers emerged in South Africa, including Takealot.com, Superbalist.com and Zando (Van Niekerk, 2020: 65). Additionally, more traditional brick-and-mortar retailers, such as Mr Price, Edgars and Truworths, launched online stores in 2016, with many of these stores now offering mobile shopping apps as well.

According to Goga et al. (2019: 14) and Lappeman et al. (2021: 100), South Africa is home to four different types of online retailers: pure-play e-tailers (online only), omnichannel retailers (or bricks-and-clicks), marketplaces and classifieds. Pure-play e-tailers are virtual retailers that focus solely on providing a range of products directly to consumers through e-commerce without maintaining a physical store (DeVry University, 2012). The largest pure-play retailers in South Africa are Takealot.com, Superbalist.com and Zando (Goga et al., 2019: 14). Bricks-and-clicks or omnichannel e-tailers, on the other hand, operate both an online store and a physical retail outlet (Ecommerce-platforms, 2021). Many larger South African retailers offer an omnipresence, such as Woolworths, Makro, @Home, Dis-Chem, Exclusive Books and Clicks. Both pure-play and omnichannel retailers offer drop-off point deliveries and click-and-collect services, where the customer places their order online, but opts to collect their order from a preferred retail store. Marketplaces provide the online infrastructure for other sellers to sell their products, for example Bid or Buy and Hello Pretty. These platforms either require the seller to ship their products to a central warehouse for fulfilment or allow the reseller to ship independently (Goga et al., 2019: 14). Lastly, classifieds are similar to a marketplace, but allow customers to place small advertisements for products and services of a single item online for other end users to purchase. Well-known classified websites in South Africa include OLX, Gumtree and Facebook Marketplace (Goga et al., 2019: 15).

Based on the four major categories mentioned above, Figure 2.9 displays some of the most renowned retailers in South Africa that sell consumer goods and offer mobile apps. Online retailers might be generalists that sell across multiple categories (multi-category retailers), such as Takealot.com, or specialised retailers that focus on particular product categories such as pet care, home goods, sportswear, or health and wellness (Lappeman et al., 2021: 100).

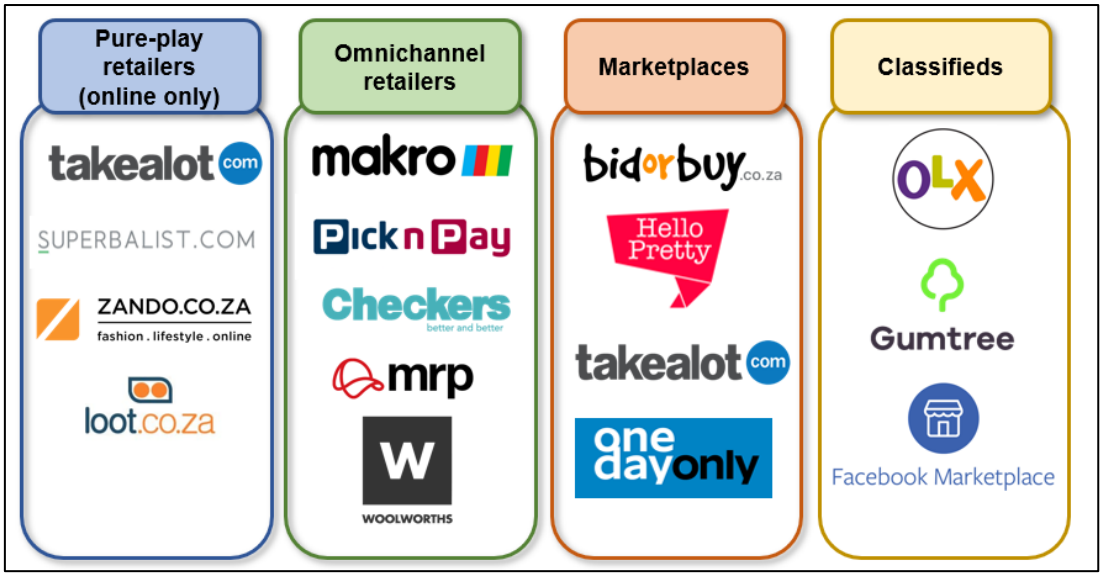

Figure 2.9: Renowned retailers offering mobile shopping apps in South Africa
Source: Author's own compilation

The research study concentrated on omnichannel retailers supplying food and groceries due to their significance in the retailing industry and novelty in the South African market. Omnichannel retailing involves "… an integrated sales experience that melds the advantages of physical stores with the information-rich experience of online shopping" (Rigby, 2011 in Sroka, 2020: 267). It therefore requires the provision of a coordinated operating business and marketing model in which all the retailer's channels are aligned and communicate a single and cohesive image to the customer (Sroka, 2020: 268). Omnichannel retailers, especially in the grocery and food delivery service sector, have recently adapted their business models to meet the needs of the on-demand consumer market. The on-demand industry has long been served by a variety of fast-food delivery apps, but grocery retailers in South Africa have recently expanded their market with comparable cutting-edge mobile app business models and offers.

The burgeoning on-demand economy which ultimately led to the advent of same-day delivery mobile apps will be explored in the next section. This is the focus of the research study.

2.5 THE ON-DEMAND ECONOMY: AN EMPHASIS ON SAME-DAY DELIVERY APPS

The thriving on-demand economy, also referred to as the 'access economy', which allows users to order a wide range of products and services from the comfort of their own space and with their smart device, has changed the face of modern commerce (Zhong, 2021: 158). The on-demand

economy is described as "… the economic activities created by digital marketplaces and technology companies to fulfil consumer demand via immediate access to goods and services" (Hanks, 2018). Through an online marketplace where individuals can effortlessly sell and buy goods and services without time restrictions, the on-demand economy strives to give users access to their chosen goods and services (Jain, 2022). On-demand service apps are used in an increasing number of economic activities, enabling both large and small business owners to reach a wider client base and draw in both young and old (Zhong, 2021: 158).

Many consumers worldwide already make use of on-demand services. According to Zhong (2021: 158), in 2020, the on-demand economy attracted more than 22.4 million US users who spent US$57.6 billion using different on-demand service apps. What started as the fastest way to hail a taxi, Uberisation, has changed the way businesses perceive demand, provision the supply and deliver (Mansuri, 2021). Since then, many on-demand services have emerged, including services from tourism and accommodation (Airbnb) to fuel delivery (Filld), healthcare services (On-demand Doctor), professional services (mechanics, pest control, electricians, plumbers and au pairs) and food delivery services (Just Eat, Delivery Hero, GrubHub etc.) (Mansuri, 2021).

The on-demand service delivery market has been clustered into seven broad categories, namely transportation, healthcare and telemedicine, fitness, beauty, entertainment, home services and food and grocery delivery (Vilmate, 2021):

1. On-demand transportation services involve passenger ride-hailing facilities such as those offered by Uber and Lyft, where an individual can request a car ride service by indicating their current and desired drop-off location on a mobile app. This category furthermore includes professional on-demand services from a mechanic or tow truck service, fuel delivery, car wash and car rental services (Faisal, 2021).

2. On-demand healthcare and telemedicine services safely and securely connect individuals seeking medical consultation with medical professionals capable of providing it on a mobile app. These services include a doctor on demand, which allows medically certified doctors to consult with patients via video conferencing calls, offer medical advice and prescribe medication.

3. On-demand fitness services offer a personal trainer functionality on a user's smart device where users can receive personalised and live-streaming fitness instructions from the trainer.

4. Beauty-on-demand services allow users to book an appointment at a beauty salon or spa, or receive any skincare and wellness services in the comfort of their home on the same day. This category involves booking professional beauty specialists for various in-home or on-site appointments, such as a makeup artist, hairstylist, or nail technician.

5. On-demand entertainment services generally include live video streaming services, for instance Netflix, YouTube, Disney+ and Amazon Prime. These on-demand services allow the user to livestream a wide range of movies and series, either for free or a small monthly subscription fee. The revenue of the video-on-demand industry was worth US$34.78 million in 2020 and is constantly increasing (Faisal, 2021).

6. The on-demand home services industry grants users access to a large pool of registered professionals who will take care of their homes, children and pets. This category includes professional services related to repair and maintenance, home care and design, wellness, au pair, pet sitters, and many other services.

7. On-demand food and grocery deliveries include on-demand delivery services from restaurants and fast food outlets, as well as grocery store retailers to the user's chosen delivery address within the same day or a few hours. This category will be explored in more detail below.

With the advent of the on-demand economy, e-tailers have created innovative delivery options, such as same-day delivery or delivery within an hour, to improve the overall customer experience (Ajmeri & Vohra, 2019: 91), which has ultimately led to the development of a new facet of the on-demand economy – same-day delivery. Due to the high demand from customers reluctant to physically visit brick-and-mortar stores as a result of the global COVID-19 pandemic in 2020, same-day food delivery apps, also known as on-demand food delivery apps, quickly gained popularity among retailers and customers. As a result, many businesses enforced a same-day delivery business model, which is still in its early stages of development.

The concept of same-day delivery dates back many eras when door-to-door hawkers and pedlars delivered milk directly to consumers' doorsteps. From the early 20th century, butchers, bakers and grocers offered home deliveries within their local catchment. However, these services were pre-arranged or recurring orders. Ad hoc same-day delivery orders and deliveries were only possible from door-to-door salesmen (Allen, Piecyk & Piotrowska, 2018: 3). The Internet, along with online and mobile commerce, has transformed consumer retail ordering patterns and opened up many new avenues for same-day delivery. Many businesses, such as UrbanFetch, Kozmos and

Webvan, identified same-day delivery as an opportunity but failed to build a sustainable business model around it (Hausmann, Herrmann, Krause & Netzer, 2014). Nevertheless, same-day delivery services have expanded significantly over the past few years, particularly as a response to the COVID-19 outbreak, including takeaway meal deliveries, grocery retailing and non-food retailing (Allen et al., 2018: 3).

Same-day delivery apps, also known as on-demand food delivery apps, are smartphone platforms that let customers place orders with independent service providers or agents and have their purchases delivered on the same day. Same-day delivery apps aim to reduce the delivery time of selected products to the same day to give customers instant gratification (Jain, 2022). In the context of the research study, 'same-day delivery' refers to meal deliveries from fast-food outlets and/or restaurants and products from grocery stores that take place on the same day the order was placed. The terminology used by authors to describe these same-day deliveries includes instant deliveries, on-demand deliveries, on-demand logistics, or rush deliveries (Allen et al., 2018: 3). For the purpose of the research study, 'same-day delivery apps' is used.

A summary of the same-day delivery app market from a worldwide viewpoint is first provided in the following section, followed by an overview of the same-day delivery app industry of South Africa.

2.5.1 GLOBAL PERSPECTIVE ON THE SAME-DAY DELIVERY APP MARKET

Online food delivery is reported to be the largest market segment in retail e-commerce (Ali, Khalid, Javed & Islam, 2020: 1), which was substantially increased by the worldwide COVID-19 pandemic in 2020 (Amin et al., 2020: 2). COVID-19 has impacted the daily life of many people globally (Grashuis, Skevas & Segovia, 2020: 1). To prevent the virus from spreading during the global pandemic, individuals were prohibited from attending large social events and, wherever possible, avoided retail establishments and restaurants (Grashuis et al., 2020: 1). As a result, consumers began to request home delivery services more frequently. The shift in customers' food buying behaviour has spurred the growth of the grocery and food delivery industry considerably (Chotigo & Kadono, 2021: 1).

Food delivery apps have become more popular, which is reviving the food and grocery industry (Chotigo & Kadono, 2021: 1). There are currently numerous food- and grocery-related same-day delivery apps available globally (Allen et al., 2018: 25; Xi et al., 2020: 35). Amazon, Uber Eats,

Deliveroo, Delivery Hero, Just Eat, Foodpanda, Postmates, Walmart, Instacart and Grub Hub are some of the key participants in the global food delivery app market.

The food delivery services industry is a billion-dollar industry, with China accounting for one-third of the worldwide food delivery apps revenue in 2019 (US$95 billion), followed by the USA, UK and India (Muangmee et al., 2021: 1298; Ribeiro, 2018: 9). With a 6% global penetration rate in 2018, the platform-to-consumer food delivery market had already reached a total value of US$17.4 million (Ribeiro, 2018: 9). The online food delivery market was estimated at US$136.4 billion in more recent statistics (January 2021), with an annual change in total value of 27%. Of the 1.2 billion individuals reported to have used online services to order takeaway food in 2021, the yearly revenue per user of online delivery services worldwide was US$112 billion (Hootsuite, 2021: 258). By 2024, it is anticipated that the global market for online food delivery will amount to US$164 billion (Muangmee et al., 2021: 1298). With China dominating the market share, food delivery services through smartphone apps have become a global trend. The growth of food delivery services to new markets is based on the cultivation of consumers' eating habits and evolving fashion trends (Muangmee et al., 2021: 1298).

Consumers in industrialised countries, particularly in the USA, spend roughly US$57.6 billion on the on-demand economy, a modest portion (7.98% or US$4.6 billion) of which is spent on food and grocery deliveries (Kumar, 2020). In the UK, the online grocery and food shopping market was estimated to have generated total annual sales of £9.9 billion in 2016, which accounted for 6.1% of all grocery sales in the UK (Allen et al., 2018: 25). Furthermore, according to Xi et al. (2020: 35), 46% of all Internet users in China were same-day delivery online consumers in 2018, who numbered 364 million.

The South African same-day delivery app market is more thoroughly examined in the next section, compared to global data.

2.5.2 THE SOUTH AFRICAN SAME-DAY DELIVERY APP MARKET

The most widely used same-day delivery apps available in South Africa are food- and grocery-related same-day delivery apps and were therefore the focal point of the research study. Online food delivery services refer to any food delivery, with monetary value, that is ordered through a mobile handheld device such as a smartphone (Prasetyo, Tanto, Mariyanto, Hanjaya, Persada, Miraja & Redi, 2021). Orders can be placed either directly with the retailer or restaurant (e.g. Burger King, Pizza Hut, Checkers Sixty60, Pick n Pay ASAP!), or by using a third-party or

intermediary app (e.g. Uber Eats, OneCart, CartRun, Mr D Food) (Arsiwala, 2020: 8; Ribeiro, 2018: 9). Third-party apps generally involve multiple retailers subscribing to the service offered by the third party, allowing the user to browse and select between various retailers (Arsiwala, 2020: 8). Retailers and restaurants can register their business with these third-party apps, allowing customers to view the food or products offered by the business through the compound mobile app. Orders placed by customers are delivered by using the logistical support of online delivery companies. Customers enjoy the convenience of having food or products delivered to their preferred address from a variety of retailers or restaurants, and retailers benefit from increased business exposure and sales (Arsiwala, 2020: 8).

The research study's focus was on food- and grocery-related same-day delivery apps because they are the most widely used on-demand delivery services in South Africa. Ordering through same-day delivery apps can be done either directly from the retailer or food outlet (restaurant or fast food outlet), or through an intermediary or third-party mobile app. Customers who place orders with third parties do so online through an intermediary, such as Mr D Food, Uber Eats or OneCart, which often enables users to explore and select among numerous stores or outlets from a single app. The intermediary arranges for pickup and delivery of the order to the users' preferred address after notifying the store or outlet to prepare the order. To use the services and functions of the third-party mobile app and to reach a much larger audience, retailers or outlets typically pay a subscription fee.

Although the same-day delivery app market in South Africa is still in its infancy (during the time the study was conducted), with the first grocery-related same-day delivery app being launched in 2019, the onset of the COVID-19 pandemic accelerated the development and implementation of these apps globally. Furthermore, South African food and grocery businesses had to quickly adjust to the significant change in consumer purchasing behaviour brought on by the COVID-19 pandemic and modify their business models to include a same-day delivery option (Business Tech, 2021b).

Many food and grocery delivery apps with same-day delivery options are available in South Africa. These mobile apps are categorised as either grocery retailers, food establishments including fast-food outlets and sit-down restaurants, or 'other' retailers with a same-day delivery option. Each category can be further grouped as either purchasing directly from a single specific retailer (direct), or through the use of a third-party intermediary app (indirect).

Figure 2.10 displays some of the most popular same-day delivery apps that are accessible in South Africa.

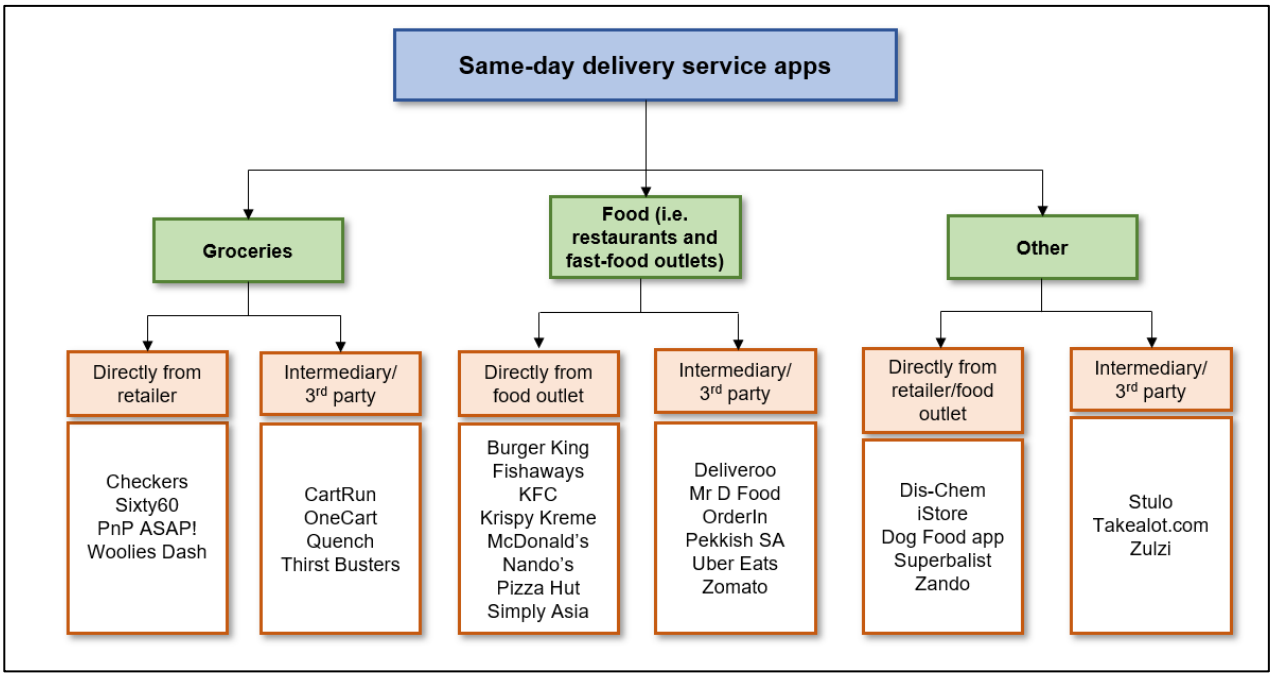

Figure 2.10: Categories and sub-categories of same-day delivery apps in South Africa
Source: Author's own compilation

Each of the same-day delivery app categories available in South Africa, as depicted in Figure 2.10, will be discussed in more detail below.

2.5.2.1 Grocery-related same-day delivery apps

In South Africa, the number of on-demand delivery services that deliver groceries to consumers' doors has begun to rise (Fatoki, 2020: 1). Supermarkets promote e-tailing because of the rising number of smartphone users, high connectivity, contactless technology and improved Internet or mobile data access, which allow customers to experience shopping differently from the traditional in-store services. M-commerce has substantially changed how consumers shop for groceries. Retailers are enticing customers with new, cutting-edge shopping platforms and delivery alternatives as a result of their recognition of the significance of the trend towards on-demand service delivery (Fatoki, 2020: 1). For retailers to perform better, m-commerce should, according to researchers, be a crucial component of their omnichannel strategy (Chao, Ping & Wang, 2019: 41; Fatoki, 2020: 1; Knežević & Delić, 2017: 44).

Some of the largest grocery retail chains in South Africa, such as Checkers, Pick n Pay and Woolworths Food, quickly responded to the transforming shopping community, especially after the start of the worldwide COVID-19 pandemic, by adapting, partnering with and launching same-day delivery apps. The first grocery-related same-day delivery app in South Africa ('Sixty60'), was released by Checkers, a division of Shoprite Holdings Ltd, in November 2019 (Shoprite, 2019). With the help of the Checkers Sixty60 mobile app, customers can order groceries and liquor online for delivery within 60 minutes and at the same great value for money that Checkers is known for. During the international COVID-19 pandemic, which increasingly bound people to their homes, both Pick n Pay and Woolworths Food created and released a comparable same-day delivery app, allowing customers to order groceries on the app and receive delivery within a few hours (Teuteberg, 2020: 8). In the early stages of COVID-19 lockdown, Pick n Pay expanded its partnership with the "Bottles" app. However, in 2021, Pick n Pay bought the platform, integrated it completely and relaunched it as Pick n Pay ASAP! (Fin24, 2021). Woolworths Food launched its trial version of Woolies Dash in December 2020, which is still only available in selected major retail stores.

A comparison of the features of each of these retailers' same-day delivery apps (i.e. Checkers Sixty60, Pick n Pay ASAP! and Woolies Dash) is given in Table 2.1.

Table 2.1: Comparison of major grocery retailers' same-day delivery apps available in South Africa

	Checkers Sixty60	**Pick n Pay ASAP!**	**Woolies Dash**
Launch date	November 2019	April 2020	December 2020
Delivery fee	R35 per order	R35 per order	R35 per order
Minimum order	R100	R100	R100
Item basket limit	35	35	30
Tracking	Live tracking; app notifications; WhatsApp updates	Real-time tracking; app notifications	Personal shopper; app notifications
Substitutional and refund option	Yes	Yes	Yes
Availability	129 participating stores in all 9 provinces	133 participating stores in 5 provinces (Western Cape, Gauteng, KwaZulu-Natal, Free State, Eastern Cape)	19 participating stores in 3 provinces (Western Cape, Gauteng, KwaZulu-Natal)
Slots	1-hour slots	1-hour slots	1-hour
Rewards integration	Yes – Xtra Savings rewards; eBucks rewards if FNB client	Yes – Smart Shopper points	No – WRewards will be possible in the future
Number of users	1.4 million	1.2 million	Unknown

	Checkers Sixty60	Pick n Pay ASAP!	Woolies Dash
Product selection	Over 15 000 products	Over 10 000 products	Unknown

Source: Business Tech (2021b); Checkers Sixty60 (2021); iAfrica (2021); Pick n Pay ASAP! (2021); Shoprite (2021); Woolworths (2021)

Products can also be ordered from grocery retailers through third-party intermediate smartphone apps in addition to direct same-day delivery apps (as discussed above). In South Africa, there are several third-party on-demand grocery app providers, as listed in Figure 2.10. One such notable and successful business is OneCart, which offers on-demand delivery services and has worked with businesses such as Pick n Pay, Woolworths Food, Mr Pet, Food Lover's Market, Dis-Chem, Clicks, Jacksons and Makro. OneCart allows customers to choose products from many stores on a single platform, instead of purchasing separately from each retailer (OneCart, 2021; Teuteberg, 2020: 8). Orders are forwarded to a dedicated OneCart concierge shopper, who collects the desired products from a variety of retailers. The purchased items are then delivered the same day to the user's designated delivery address by a delivery partner (OneCart, 2021).

Similarly, Quench is a high-end global shopping platform bringing groceries, liquor, restaurants and eateries directly to the homes of the user (Quench, 2021). CartRun also allows a user to shop from one of its trusted partners, including Woolworths Food, Pick n Pay and Clicks, and have the products delivered within 2 hours (CartRun, 2021).

2.5.2.2 Food-related same-day delivery apps (restaurants and fast-food outlets)

Food-related apps, which include deliveries from fast-food outlets and restaurant partners, make up the second category of same-day delivery services, as shown in Figure 2.10. Food-related same-day delivery apps are divided into ordering directly from a specific food outlet (direct), or through a third-party mobile app (indirect). In South Africa, many direct food-related same-day delivery apps allow customers to place orders with the restaurant or fast-food outlet directly. Burger King, Debonairs Pizza, Fishaways, KFC, Krispy Kreme, McDonald's, Nando's, Pizza Hut, Simply Asia and Steers are a few examples of food-related same-day delivery apps in South Africa.

Customers were not permitted to sit down at restaurants during South Africa's lockdown restrictions enforced in March 2020 due to the COVID-19 outbreak and could only order takeout or home deliveries (Von Ulmenstein, 2020). Lockdown restrictions ultimately led to an increase in

the number of restaurants and fast-food outlets adopting third-party delivery services to reach a wider audience and make up for lost revenue. Uber Eats, Mr D Food and Zomato are some of the best-known third-party companies in South Africa that deliver food from several eateries. South Africa's online food delivery industry was worth R10.49 billion in 2019 and an expected growth rate of 14% is forecasted to reach R17.6 billion by the end of 2023 (Toyana, 2020).

One of the largest and most well-known food delivery service in South Africa, Uber Eats, has collaborated with several restaurants and fast-food outlets across the country, allowing customers to select from a variety of eateries on a single app. The online food ordering and delivery app experienced a positive surge in 2020. Revenue from Uber Eats South Africa was roughly R67.5 billion, compared to the R26.7 billion generated in 2019 (Maleke, 2021). Since its launch in 2016, Uber Eats recorded 2.1 million app downloads (Toyana, 2020), serving over 700 000 active monthly users in the country (Babatunde, 2021).

Uber Eats' largest rival, Mr D Food, is a call-and-deliver service that was established in the early 1990s and is run by Takealot.com, a well-known e-commerce retailer in South Africa. The Mr D Food app, which boasts 700 000 active monthly users and processes an average of R1.5 billion in food orders yearly, has been downloaded by about 2 million South Africans (Toyana, 2020). Between the two largest food delivery rivals in South Africa, Uber Eats and Mr D Food captured about 80% to 90% of South Africa's food-hailing market (Toyana, 2020).

Zomato, which connects customers to restaurants and delivery partners, debuted in 2010 and is currently the third most popular intermediary food delivery service in South Africa. Zomato offers the same ordering and delivery services provided by Uber Eats and Mr D Food, but also offers additional services, such as discovering restaurants, making reservations and making payments while dining at the restaurant (Zomato, 2021).

2.5.2.3 'Other' same-day delivery apps

Other renowned retailers that provide a same-day delivery option include Takealot.com, Apple iStore, Zando, Superbalist.com and the Dog Food App, to name but a few. Examples of third-party same-day delivery apps are Stulo and Zulzi, which allow users to find multiple categories of stores ranging from groceries, pharmaceuticals, household appliances and products, and restaurants on a single app (Stulo, 2021; Zulzi, 2021). As the focal point of the research study was on the delivery of food and groceries through same-day delivery apps, these categories are not further elaborated on.

Many businesses are being compelled by the accelerating pace of digital technology to fulfil the innovative and challenging demands of their customers for timely marketing (Dahlström & Edelman, 2013). In an on-demand world, customers tend to criticise brands based on their ability to deliver heightened experiences and interactions that offer high levels of value and are personalised and easy to access. Therefore, it has become crucial for companies to use cutting-edge business and marketing techniques to satisfy consumer demand.

Even though the South African online retailing industry has grown significantly during the past few years, especially with the onset of the worldwide COVID-19 pandemic, only a small portion of the country's retail market currently offers same-day delivery apps (Babatunde, 2021; Maleke, 2021; Toyana, 2020). The implementation of a same-day delivery app business model may be hampered by several adaptation challenges, particularly for informal businesses with staffing restrictions, manual or inefficient dispatching and routing, high costs and inadequate infrastructure and knowledge (Listaso Technology, 2023). Same-day delivery apps have only recently emerged in the South African retailing industry and are offered primarily by large retailers that have the required resources, support and infrastructure to operate these apps successfully (Fatoki, 2020: 1).

A key question arising from the current state of the on-demand economy in South Africa is what factors influence consumers' behavioural intention to continue using these same-day delivery apps, specifically in the food and grocery app category. The research study aimed to answer this question.

2.6 CONCLUSION

Chapter 2 offered context that served as the definitive boundary of the research study. It is evident from the discussion in this chapter that, during the past few years, there has been a significant revolution in customer trends and behaviour due to the development of mobile technology and the emergence of the on-demand economy. The on-demand economy has rapidly taken over the traditional business paradigm by offering customers products and services whenever they demand them, without having to leave the comfort of their homes. The rapid growth of the on-demand economy was brought about by the advancements of innovative mobile technology and mobile apps. The technology advancements, together with today's accelerated lifestyle and intense use of technologies encourage customers to purchase through mobile apps. People are constantly searching for new alternatives to simplify daily tasks and modify them to fit their lifestyle. Mobile apps are an essential part of everyday life. The ubiquity of smartphones, high-speed Internet

access, improvements in personalised and interactive apps and the quick pace of modern life have all contributed to the favourable environment for the uptake of mobile apps.

Chapter 2 offered an extensive overview of the rise and fast-paced development of the e-commerce and m-commerce industries, with specific emphasis on the emergence and significance of mobile shopping apps and the same-day delivery app market. The aim was to contextualise the research study by providing background information and explaining the workings of same-day delivery apps within the South African market. Many South Africans have started shopping across various channels, including mobile shopping apps; they are becoming more adept at using technology and expect their preferred retailer to provide multiple channels through which they can engage and purchase from (Van Niekerk, 2020: 76), including on-demand services.

Despite the fact that South Africa's same-day delivery app market is still in its infancy, particularly in the grocery sector, it has grown at an astounding rate since its launch in 2019. By using and extending the UTAUT2 Model, the research study sought to identify the variables that affect South African customers' behavioural intention to continue using these same-day delivery apps. By providing a better understanding of the key factors that influence consumers' behavioural intention to continue using same-day delivery apps, it is anticipated that the research study's findings will aid retailers in developing a successful and consumer-centric same-day delivery app in the South African retailing landscape.

In terms of the literature review, the following research objective was achieved in Chapter 2:

Research objective 1: To discuss mobile apps and same-day delivery app usage from an international and South African context and in relation to the retailing industry.

In Chapter 3, the development of the UTAUT and UTAUT2 Models is explored by conceptualising the constructs included in the development and validation of the models and highlighting the limitations and strengths of the UTAUT2 Model in determining behavioural intention.

CHAPTER 3:
THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY MODELS (UTAUT AND UTAUT2)

3.1 INTRODUCTION

In an era marked by the fast-paced growth of the on-demand economy, it is essential for retailers to modify traditional business models and offer customers products and services when and where they demand them. The rapid evolution of consumer behaviour, coupled with a growing demand for instantaneous product delivery via same-day apps, highlights the fundamental need for investigating the intentions behind consumers' adoption of new technological systems and devices, which has emerged as a key research focus in the field of information technology (Miladinovic & Xiang, 2016: 12; Momani & Jamous, 2017: 51).

Acceptance of new technology is often referred to as one of the most mature research areas in contemporary information systems literature and thus, research in this area has resulted in several theoretical models, with origins in information systems, sociology and psychology (Venkatesh et al., 2003: 425). As a result, many competing models have been developed, each with different constructs determining behavioural intention and user acceptance of new technologies. Venkatesh et al. (2003: 425) argue that researchers are confronted with the decision to choose between several competing technology acceptance models and many latent variables. Seminal authors Venkatesh et al. (2003: 425) consequently endeavoured to consolidate several well-established technology acceptance theories into one integrated model. The purpose of Venkatesh et al.'s (2003) research undertaking was to review the extant user acceptance models readily available in the literature, empirically compare eight existing theoretical models, formulate a unified model and empirically validate the consolidated UTAUT Model. The aim was to understand usage as the dependent construct.

In Chapter 3, the purpose and development of the UTAUT and UTAUT2 Models are explained. The constructs of the UTAUT Model, the moderators as well as a theoretical analysis and limitations of the model will be discussed. The UTAUT2 Model, which was developed to address the shortcomings of the original UTAUT Model, will be discussed by explaining the additional constructs and moderators incorporated to develop a unified model of behavioural intention and actual behaviour from a consumer perspective. The ultimate purpose of Chapter 3 is to assess the scientific and methodological rigour of the UTAUT2 Model and to establish its significance in

determining consumers' behavioural intention for the purpose of the research study (literature research objective 2).

3.2 ROLE OF THEORETICAL FRAMEWORKS

Exploring individuals' adoption, acceptance and use of information technology and information systems has been documented since the early 1970s, because it is considered a requirement for understanding the utilisation of technology (Momani & Jamous, 2017: 51). Consequently, many theories and models have emerged from several research undertakings over the years to explain individuals' usage and adoption behaviour towards various technologies (Wentzel, Diatha & Yadavalli, 2013a: 2). Some of these well-known models that have been widely applied and reapplied in research include Innovation Diffusion Theory (IDT) (Rogers, 1962), Technology Acceptance Models (TAM, TAM2 and TAM 3) (Davis, 1989; Venkatesh & Davis, 2000; Venkatesh & Bala, 2008), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Theory of Reasoned Action (TRA) (Ajzen, 1975), model of PC utilisation (MPCU) (Thompson, Higgins & Howell, 1991), motivational model (MM) (Davis, Bagozzi & Warshaw, 1992) and the Unified Theory of Acceptance and Use of Technology Models (UTAUT and UTAUT2) (Venkatesh et al., 2003; 2012), to name but a few. These technology acceptance models and adoption behaviour theories aim to explain how individuals may understand and use new technology (Momani & Jamous, 2017: 51).

Technology acceptance research is often described as one of the most established research areas and, as such, has resulted in the development of several theoretical models (Venkatesh et al., 2003: 426). Research has, however, proven that selecting the most appropriate theory in information systems research remains a critical task for researchers (Al-Mamary et al., 2016: 143). The literature on technology acceptance theories confirms that existing models have different premises and benefits in determining behavioural intention or planned behaviour (Samaradiwakara & Gunawardena, 2014: 29). The UTAUT2 Model, however, has been proven to be more robust in assessing and predicting individuals' behavioural intention to accept and use technology in various contexts and settings. The UTAUT2 therefore provides a reliable foundation to explain consumers' behavioural intention to adopt or reject a new technology (Dwivedi et al., 2017: 719; Moghavvemi et al., 2013: 247; Taiwo & Downe, 2013: 48). It offers many latent possibilities in enhancing researchers' understanding of technology acceptance in a consumer context (Samaradiwakara & Gunawardena, 2014: 29).

3.3 THE UTAUT MODEL

Recognising the wide variety of competing technology acceptance models and latent constructs available to researchers, Venkatesh et al. (2003: 425) sought to consolidate several well-established technology acceptance theories into one integrated model. The purpose of Venkatesh et al.'s research undertaking was to review the extant user acceptance models readily available in the literature, empirically compare eight existing theoretical models, formulate a unified model and empirically validate the consolidated UTAUT Model. The aim was to understand usage as the dependent construct.

Eight widely employed and competing technology acceptance theories were identified in Venkatesh et al.'s review (2003: 428-432) of existing technology acceptance literature. The eight theories integrated to develop and validate the UTAUT Model were the following:

- Innovation Diffusion Theory (IDT) in 1962 by Everett M. Rogers
- Social Cognitive Theory (SCT) in 1986 by Albert Bandura
- Theory of Reasoned Action (TRA) by Martin Fishbein and Icek Ajzen in 1975
- Technology Acceptance Model (TAM) by Fred D. Davis in 1989
- Theory of Planned Behaviour (TPB) in 1991 by Icek Ajzen
- Model of PC Utilisation (MPCU) in 1991 by Ronald L. Thompson, Christopher A. Higgins and Jane M. Howell
- Motivational Model (MM) by Fred D. Davis, Richard P. Bagozzi and Paul R. Warshaw in 1992
- A model combining the TAM and TPB, namely C-TAM-TPB by Shirley Taylor and Peter A. Todd in 1995

Table 3.1 describes the eight theories listed above and defines the constructs embodied in each of these theories. The theories discussed in Table 3.1 hypothesise between two and seven constructs each which potentially impact the acceptance of technology. A total of 32 independent constructs, across these eight theories, are discussed.

Table 3.1: Models and theories of technology acceptance

Model/theory	Determinants/ constructs	Definition
Innovation Diffusion Theory (IDT) (Rogers, 1962)		
IDT has been used since the 1960s to study the adoption of a variety of behaviours, ideas, products and technologies in numerous fields of study, ranging from agriculture to organisational innovation (Venkatesh et al., 2003: 431). Moore and Benbasat (1991) adopted the characteristics of innovation presented by Rogers in 1962 and developed a set of constructs within the information systems domain that could be used to explore individual technology acceptance within organisations.	Relative advantage	"The degree to which an innovation is perceived as being better than its precursor". Taken from Rogers (1962).
	Ease of use	"The degree to which an innovation is perceived as being difficult to use" (Moore & Benbasat, 1991: 195).
	Image	"The degree to which use of an innovation is perceived to enhance one's image or status in one's social system". Taken from Rogers (1962).
	Visibility	The degree to which one can see others using the system in the organisation (Adapted from Moore & Benbasat, 1991).
	Result demonstrability	"The tangibility of the results of using the innovation, including their observability and communicability" (Moore & Benbasat, 1991: 203).
	Compatibility	"The degree to which an innovation is perceived as being consistent with the existing values, needs, and past experiences of potential adopters". Taken from Rogers (1962).
	Voluntariness of use	"The degree to which use of the innovation is perceived as being voluntary or of free will" (Moore & Benbasat, 1991: 195).
Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975)		
TRA was introduced to understand the relationship between individual beliefs, attitudes, intention and behaviour (Tlou, 2009: 16). The theory suggests that individuals' behavioural intention is affected by two major factors, namely individuals' attitudes towards performing the given behaviour and the subjective norms associated with the behaviour (Jen, Lu & Liu, 2009: 91; Tlou, 2009: 16).	Subjective norm	"The intention of the individual to use a technology based on the opinion of the social groups that are of importance to the individual and that approves or disapproves of the technology and/or behaviour" (Fishbein & Ajzen, 1975: 302; Miladinovic & Xiang, 2016).
	Attitude towards behaviour	"The individual's positive or negative feelings (evaluative effect) about performing the specific behaviour" (Fishbein & Ajzen, 1975: 216).

Model/theory	Determinants/ constructs	Definition
Social Cognitive Theory (SCT) (Bandura, 1986)		
SCT, originally developed by Bandura in 1986, defines human behaviour as a triadic, dynamic and reciprocal interaction of personal factors, behaviour and the environment (Al-Mamary et al., 2016: 145). Compeau and Higgins (1995) applied and extended SCT to the context of computer utilisation and identified five core constructs, namely outcome expectations (performance), outcome expectations (personal), self-efficacy, affect and anxiety. They examined computer use, but Venkatesh et al. (2003) assessed the model's predictive validity in terms of intention and usage to allow for a fair comparison of the models.	Outcome expectations – performance	"The performance-related consequences of the behaviour. Specifically, performance expectations deal with job-related outcomes" (Compeau & Higgins, 1995 in Venkatesh et al., 2003: 432).
	Outcome expectations – personal	"The personal consequences of the behaviour. Specifically, personal expectations deal with the individual esteem and sense of accomplishment" (Compeau & Higgins, 1995 in Venkatesh et al., 2003: 432).
	Self-efficacy	"Judgement of one's ability to use a technology to accomplish a particular job" (Venkatesh et al., 2003: 432).
	Affect	"An individual's liking for a particular behaviour" (Venkatesh et al., 2003: 432).
	Anxiety	"Evoking anxious or emotional reactions when it comes to performing a behaviour" (Venkatesh et al., 2003: 432).
Technology Acceptance Model (TAM) (Davis, 1989)		
TAM initially originated from the TRA that was used in social psychology to explain a wide range of individual behaviours (Gong & Yan, 2004: 445). The main goal of TAM is to provide a universal description of the factors that influence technology acceptance and explain the behaviour of technology users across a broad range of technological devices/systems and among various user populations (Davis et al., 1989: 895). TAM was specifically developed to be used within the information systems domain and predicts the behavioural intention and the use of information technology in a workplace environment (Alghariبi & Arvanitis, n.d.: 527; Davis, 1989: 139; Wentzel et al., 2013a: 3). TAM2 enhanced TAM by incorporating subjective norm as an additional predictor of intention in the case of mandatory setting (Venkatesh & Davis, 2000). TAM has been widely used across a wide range of technologies and users.	Perceived usefulness	"The degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989: 320).
	Perceived ease of use	"The degree to which the prospective user expects the target system to be free of effort" (Davis, 1989: 320).
	Subjective norm	Adapted from TRA/TPB. Included in TAM2 only.

Model/theory	Determinants/ constructs	Definition
Theory of Planned Behaviour (TPB) (Ajzen, 1991)		
The TPB expanded the TRA to address the original model's limitation in dealing with behaviours over which individuals have partial volitional control (Ajzen, 1991: 181). To explain an individual's behavioural intention, Ajzen (1991: 181) included the construct of 'perceived behavioural control'.	Attitude towards behaviour	"The individual's positive or negative feelings (evaluative effect) about performing the specific behaviour" (Fishbein & Ajzen, 1975: 216). Adapted from TRA.
	Subjective norm	"The intention of the individual to use a technology based on the opinion of the social groups that are of importance to the individual and that approves or disapproves of the technology and/or behaviour" (Fishbein & Ajzen, 1975: 302; Miladinovic & Xiang, 2016: 13). Adapted from TRA.
	Perceived behavioural control	"The perceived ease or difficulty of performing a particular behaviour" (Ajzen, 1991: 188). In the context of information systems research, perceived behavioural control refers to the internal and external constraints on behaviour (Taylor & Todd, 1995: 149).
Model of PC Utilisation (MPCU) (Thompson, Higgins & Howell, 1991)		
The MPCU is grounded in the early work of Triandis (1979), who argued that behaviour is determined by what people like to do (attitude), what they think they should do (social norms), what they have usually done (habits) and by the expected consequences of behaviour (in Thompson et al., 1991: 126). The MPCU test is a subset of Triandis' theory applied to the context of PC utilisation (Thompson et al., 1991: 126). Thompson et al. (1991: 126) sought to predict usage behaviour rather than intention; however, to compare the various models, Venkatesh et al. (2003: 430) examined the effect of these determinants on intention.	Job-fit	"The extent to which an individual believes that using a technology can enhance the performance of his or her job" (Thompson et al., 1991: 129).
	Complexity	"The degree to which an innovation is perceived as relatively difficult to understand and use" (Thompson et al., 1991: 128).
	Long-term consequences	"Outcomes that have a pay-off in the future" (Thompson et al., 1991: 129).
	Affect towards use	Based on Triandis (1979), affect towards use refers to the "… feelings of joy, elation, or pleasure, or depression, disgust, displeasure, or hate associated by an individual with a particular act" (Thompson et al., 1991: 127).
	Social factors	Derived from Triandis (1979), social factors refer to an "… individual's internalisation of the reference group's subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Thompson et al., 1991: 126).
	Facilitating conditions	"Provision of support for users of PCs may be one type of facilitating condition that can influence system utilisation" (Thompson et al., 1991: 129).

Model/theory	Determinants/ constructs	Definition
Motivational Model (MM) (Davis, Bagozzi & Warshaw, 1992)		
The MM holds that system use is determined by intrinsic (hedonic) and extrinsic (instrumental) motivations that shape the behaviour of the user (Sharma & Mishra, 2014: 22; Taherdoost, 2018: 964).	Intrinsic motivation	"The perception that users will want to perform an activity for no apparent reinforcement other than the process of performing the activity per se" (Davis et al., 1992: 1112; Venkatesh et al., 2003: 456).
	Extrinsic motivation	"The perception that users will want to perform an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself, such as improved job performance, pay, or promotions" (Davis et al., 1992: 1112; Venkatesh et al., 2003: 448).
Model Combining the Technology Acceptance Model and Theory of Planned Behaviour (C-TAM-TPB) (Taylor & Todd, 1995)		
The C-TAM-TPB model combines two predictors of the TPB (subjective norm and perceived behavioural control) with the 'perceived usefulness', 'ease of use' and 'attitudes' constructs from TAM, to provide an amalgam model (Birch, 2009: 27). Taylor and Todd (1995: 561) maintain that TAM failed to incorporate factors of society and behavioural control, which have been proven to affect actual behaviour. They therefore combined TAM and TPB to include the proven subjective norm and behavioural control variables.	Attitude towards behaviour	Adapted from TRA/TPB.
	Subjective norm	
	Perceived behavioural control	
	Perceived usefulness	Adapted from TAM.

Source: Adapted and summarised from Venkatesh et al. (2003: 428-432)

In developing the UTAUT model, and to ensure that the results were robust across various contexts, Venkatesh et al. (2003: 437) sampled for heterogeneity across technologies, organisations, industries, business functions and the nature of use (voluntary vs mandatory). In addition, perceptions of respondents were captured as their experiences with the technology increased. A questionnaire was created with Likert scale items validated in prior research and adapted to the technologies and organisations studied. Subsequent validation in a longitudinal study revealed 70% of the variance (adjusted R^2) in usage intention (Venkatesh et al., 2003: 467). The variance is an index of how values in a dataset vary from their mean or average value (McNabb, 2015: 146). A variance of 100% indicates that the model explains all the variance of the response data around the mean, and a variance of 0% indicates that the model explains none of the variability of the response data (Ogee & Ellis, 2019). Thus, the UTAUT Model is considered a broad, vigorous and influential model in technology adoption literature (Chiemeke & Evwiekpaefe, 2011: 1721; Taiwo & Downe, 2013: 48).

The empirical findings reported by Venkatesh et al. (2003: 446) in the development of the UTAUT Model provided validation for the inclusion of seven constructs that appeared to be significant determinants of behavioural intention. These seven constructs are performance expectancy, effort expectancy, social influence, facilitating conditions, computer self-efficacy, anxiety and attitude towards using the technology. However, Venkatesh et al. (2003: 446-447) theorised that only four of these seven constructs will play a significant role as direct determinants of behavioural intention, namely performance expectancy, effort expectancy, social influence and facilitating conditions. Prior research has shown that self-efficacy and anxiety are conceptually and empirically distinct from effort expectancy. Consequently, Venkatesh et al. (2003: 455) expected the same results and theorised that self-efficacy and anxiety have no direct effect on intention above and beyond effort expectancy. Furthermore, the attitudinal construct has been shown to be significant only when specific conditions are not included in the model – in the case of the UTAUT Model, constructs related to performance and effort expectancy. Empirical support suggests that affective reactions may operate through effort expectancy. Therefore, Venkatesh et al. (2003: 455) believe that any observed relationship between attitude and intention is spurious and as a result of the omission of other key predictors. This deceptive relationship likely stems from the impact of performance and effort expectancy on attitude (Venkatesh et al., 2003: 455).

Figure 3.1 illustrates the UTAUT Model as presented by Venkatesh et al. (2003: 447).

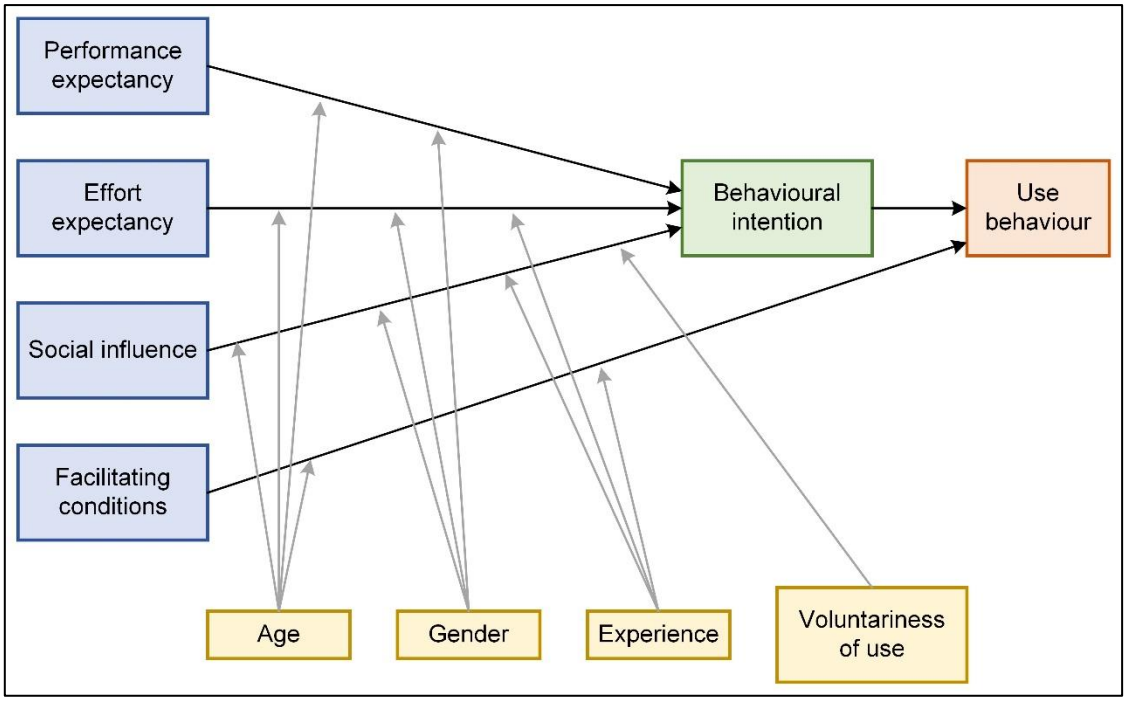

Figure 3.1: The Unified Theory of Acceptance and Use of Technology (UTAUT) Model
Source: Venkatesh et al. (2003: 447)

Behavioural intention is used at the centre of the research model as a predictor of technology usage behaviour (Thomas et al., 2013: 72). Behavioural intention refers to an individual's subjective probability to engage in a given behaviour and reflects an individual's willingness to try to perform a given behaviour (Ajzen, 1991: 181). The UTAUT Model suggests that three constructs are direct determinants of behavioural intention (i.e. performance expectancy, effort expectancy and social influence), and two constructs directly influence use behaviour (i.e. facilitating conditions and behavioural intention) (Williams et al., 2015: 444). More explicitly, performance expectancy, effort expectancy and social influence are theorised to affect an individual's intention to use technology, whereas facilitating conditions and behavioural intention to use technology are direct determinants of actual or planned technology use (Miladinovic & Xiang, 2016: 15). Four moderators were furthermore identified which are said to influence the relationship between performance expectancy, effort expectancy, social influence and behavioural intention, as well as facilitating conditions and use behaviour. The four constructs and four moderators, validated by Venkatesh et al. (2003: 457), will be contextualised in the next section.

3.3.1 CONSTRUCTS AND MODERATORS OF THE UTAUT MODEL

From the empirical analyses and validation conducted and reported by Venkatesh et al. (2003: 457-467), four constructs have been found to be significant in explaining behavioural intention and actual usage behaviours (Boonsiritomachai & Pitchayadejanant, 2017: 3). These four constructs

are performance expectancy, effort expectancy, social influence and facilitating conditions, which will be briefly discussed in the following sections.

3.3.1.1 Performance expectancy

Performance expectancy is defined as "… the degree to which an individual believes that using the system will help him/her attain gains in job performance" (Venkatesh et al., 2003: 447). Individuals are more likely to adopt new technologies when they believe this will help them to perform their job more effectively (Vermaut, 2017: 7). Performance expectancy is one of the most important constructs of behavioural intention and refers to the extent to which the usage of new technology can provide individuals with the benefits of performing specific activities (Huang & Kao, 2015: 5).

Five sub-constructs that relate to performance expectancy, which were taken from the eight incorporating models in the development of the UTAUT Model, are perceived usefulness (taken from TAM, TAM2 and C-TAM-TPB), extrinsic motivation (taken from the MM), job-fit (adapted from the MPCU), relative advantage (taken from the IDT) and outcome expectations (derived from the SCT) (Venkatesh et al., 2003: 447).

Perceived usefulness is described as "… the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989: 320). Individuals tend to either use or not use a particular technology, system or application based on their belief as to whether it will help them to perform a task more productively (Al-Mamary et al., 2016: 146).

Extrinsic motivation is defined as "… the perception that users will want to perform an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself" (Davis et al., 1992: 1112). Extrinsic motivation is driven by external rewards, such as money, social status and educational achievements. In their study, Davis et al. (1992) explain extrinsic motivation as the perceived usefulness of using the technology, and intrinsic motivation as the perceived enjoyment obtained from using the technology (in Momani & Jamous, 2017: 55).

Thompson et al. (1991: 129) describe job-fit as the extent to which an individual believes that using technology can enhance the performance of their job, such as obtaining better information for decision-making or reducing time-consuming tasks.

Relative advantage, according to Rogers' IDT (1962: 15), is a factor that influences the adoption of new technology. Relative advantage refers to "… the degree to which an innovation is perceived

as being better than the idea it supersedes" (Rogers, 1962: 213) and is often expressed in terms of economic profitability or status. Rogers' theory suggests that innovations that have a clear advantage over the previous approach will be more easily adopted and implemented (in Scott, Plotnikoff, Karunamuni, Bize & Rodgers, 2008: 2). Relative advantage therefore refers to the extent to which individuals view an innovation to be more advantageous than preceding systems or devices used to perform the same task (Makanyeza, 2017: 1000). Rogers (1962: 15) argues that the greater the perceived relative advantage of an innovation, the more rapid its rate of adoption will be.

Lastly, outcomes expectations, as embodied in the SCT refer to "… the perceived likely consequences of using computers" and are explored as having two dimensions, namely performance-related outcomes associated with improvements in job performance related to using computers, and personal outcome expectations related to expectations of change in image or status or the expectations of rewards such as promotions (Compeau & Higgins, 1991: 147). Outcomes expectations represent the anticipated performance-related or personal-related consequences, whether positive or negative, because of engaging in a given behaviour (Venkatesh et al., 2003: 432).

Similarities among these sub-constructs have been widely reported in the literature. Perceived usefulness has been described and examined as a type of extrinsic motivation as it is seen to be detrimental to achieving valued outcomes (Chan, Song, Hays & Trongmateeru, 2014: 4; Davis, 1989: 320; Ramayah, Jantan & Ismail, n.d.: 3). Thompson et al. (1991: 129) report similarities between perceived usefulness and job-fit as both are conceptualised as enhancing a person's job performance. Similarities between perceived usefulness as well as job-fit and outcomes expectations are reported by Compeau and Higgins (1995: 191), who argue that the perceived usefulness construct, measured by Davis (1989), reflects beliefs or expectations about outcomes. The perceived usefulness construct of TAM is conceptually similar to the relative advantage of innovation diffusion (Davis, 1989: 320; Yi, Fielder & Park, 2006: 398; Moore & Benbasat, 1991: 197).

Performance expectancy is one of the most important constructs of behavioural intention. Venkatesh et al. (2003: 447) proclaim that the performance expectancy construct is the strongest predictor of behavioural intention and remains significant at all points of measurement in both voluntary and mandatory settings.

3.3.1.2 Effort expectancy

The second construct validated by Venkatesh et al. (2003: 450), effort expectancy, refers to "… the degree of ease that can be associated with the use of a specific system". The construct was derived from TAM's 'perceived ease of use' construct, the IDT's 'ease of use' construct and the MPCU's 'complexity' construct (Venkatesh et al., 2003: 450).

Perceived ease of use, a well-known construct in the Technology Acceptance Models (TAM and TAM2), denotes "… the degree to which the prospective user expects the target system to be free of effort" (Davis, 1989: 320). Similarly, ease of use as utilised in the IDT refers to "… the degree to which using an innovation is perceived as being difficult to use" (Moore & Benbasat, 1991: 197). Perceived ease of use is the extent to which an individual believes that using a certain technology, system or application will be free of any effort and easy to understand (Al-Mamary et al., 2016: 146; Naiwumbwe, 2012: 12). Hamid, Razak, Bakar and Abdullah (2016: 646) argue that if a system were relatively easy to use, an individual would be more willing to learn about its features and finally intend to continue using the system. Technological innovations are generally perceived as easy to use when they are simple to learn, flexible and compatible with an individual's own needs and values (Naiwumbwe, 2012: 12). Research has shown that perceived usefulness and perceived ease of use are the main predictors of behavioural intention to use a specific system (Agrebi & Jallais, 2014: 17), and the relationship between these constructs and behavioural intention have been emphasised in numerous studies (e.g. Booker, Detlor & Serenko, 2012: 2511; Hu & Zhang, 2016: 644; Park, Nam & Cha, 2012: 602; Verkasalo, López-Nicolás, Molina-Castillo & Bouwman, 2010: 246).

The third sub-construct from existing theories capturing the effort expectancy construct in the UTAUT Model, namely complexity (derived from the MPCU), is defined as "… the degree to which an innovation is perceived as relatively difficult to understand and use" (Thompson et al., 1991: 128). Similarities among complexity, ease of use and perceived ease of use, as discussed above, are evident and have been noted in previous research (Davis, 1989: 320; Moore & Benbasat, 1991: 197; Thompson et al., 1991: 128).

Venkatesh et al. (2003: 450) found that effort expectancy is significant in both voluntary and mandatory usage contexts; however, effort expectancy becomes less significant over periods of prolonged and continuous usage of the specific technology. It is anticipated that effort-oriented constructs will be more relevant in the earlier stages of new behaviour, when process concerns represent obstacles to conquer, and later become overshadowed by matters of instrumentality (Venkatesh et al., 2003: 450).

3.3.1.3 Social influence

Social influences occur when individuals are predisposed by the thoughts, opinions, behaviours, attitudes and feelings that result from interactions with others, which are then considered to be socially acceptable behaviours, whether they be intentional or unintentional (Rashotte, n.d.). Venkatesh et al. (2012: 159) explain that social influences are the extent to which an individual perceives that important others, such as family, friends or colleagues, believe they should use a specific technology system. Social influences can be twofold as consumers are influenced either by mass media, such as newspapers, television, Internet and radio, or by their interpersonal influences, such as family, friends and colleagues (Hew et al., 2015: 1273). Chong (2013: 528) and Zhou (2012: 137) argue that when those people that are closest to an individual start using a technology or information system, the probability is high that the individual will be influenced or convinced to adopt the technology as well. Various research undertakings utilising the UTAUT Model have reported that social influence has a significant effect on behavioural intention to utilise new technologies in various contexts and industries (e.g. Alwahaishi & Snášel, 2013: 68; Chong, Chan & Ooi, 2012: 34; Hew et al., 2015: 1273; Leong, Ooi, Chong & Lin, 2013a: 2118; McKenna, Tuunanen & Gardner, 2014: 12; Miladinovic & Xiang, 2016: 22).

The social influence construct, as confirmed by Venkatesh et al. (2003: 451), is a direct determinant of behavioural intention and is represented as ‘subjective norms’ in the TRA, TPB, D-TPB and C-TAM-TPB, ‘social factors’ in the MPCU and ‘image’ in the IDT. Although the sub-constructs have different labels, each contains the unambiguous and latent notion that an individual’s behaviour is predisposed by the way in which they believe others will view them as a result of having used a technology (Venkatesh et al., 2003: 450).

In combination, as conceptualised by the TRA, TPB, D-TPB and C-TAM-TPB, subjective norms denote an individual’s perception of whether those who are important and influential to them believe they should or should not perform a certain behaviour or use a specific technology (Fishbein & Ajzen, 1975: 320; Ham, Jeger & Ivković, 2015: 740). The perceived social pressure from others and referents’ approval or disapproval of a given behaviour is determined by social norms (Miladinovic & Xiang, 2016: 13). Sanne and Wiese (2018: 4) maintain that these social pressures are frequently based on how often individuals believe that the behaviour takes place among others and the perception of the individual as to whether the behaviour of others is accepted or criticised. Subjective norms are formed out of normative beliefs and the motivation to conform to these expectations (Sanne & Wiese, 2018: 4). Normative beliefs refer to the perceived behaviour individuals expect their significant referents to display, and the motivation to comply with these expectations is based on the perceived social pressure and the individual’s willingness

to comply (Ajzen, 1991: 188; Sanne & Wiese, 2018: 4). Social norms are consequently influenced by both personal referents such as family and friends, and societal referents such as mass media (Sanne & Wiese, 2018: 4). Yanovitzky, Stewart and Lederman (2006: 8) are of the opinion that personal reference groups generally have a stronger influence on subjective norms than societal reference groups.

Thompson et al. (1991: 126) use the term 'social factors' in defining their construct and acknowledge its resemblance to subjective norms within the TRA. Social factors, as understood in the MPCU, refer to individuals' "… internalisation of the reference groups' subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations" (Thompson et al., 1991: 126). Subjective culture consists of (1) norms, which are self-instructions to do what is perceived to be correct and appropriate by members of a culture, (2) roles, which are privy to behaviours that are considered acceptable by people holding a particular position in society and (3) values – abstract categories with strong affective components (Thompson et al., 1991: 126).

Image, the last sub-construct incorporated by Venkatesh et al. (2003: 452) as a determinant of social influence, was derived from IDT and can be defined as "… the degree to which the use of an innovation is perceived to enhance an individual's image or status in their social system" (Moore & Benbasat, 1991: 195). Rogers (1962) argues that image, or the desire to gain social status, is undoubtedly one of the most important motivations for individuals to adopt an innovation (in Moore & Benbasat, 1991: 195). In the context of IDT, the image-enhancing effects of using certain technologies influence the social approval or the social structure of the individual.

3.3.1.4 Facilitating conditions

The last construct proposed by the UTAUT Model, facilitating conditions, is described as "… the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003: 453). Individuals generally look for assistance when they are using new technologies and individuals might refrain from using new technologies when facilitating conditions are inadequate (Lewis, Fretwell, Ryan & Parham, 2013: 25). Facilitating conditions are therefore the element that is solely available in the environment that has an impact on an individual's tendency to carry out a specific task (Rezaei, Shahijan, Amin & Ismail, 2016: 417).

The definition of facilitating conditions captures concepts epitomised by three different sub-constructs from various technology acceptance and usage behaviour theories, namely perceived

behavioural control (taken from TPB, D-TPB and C-TAM-TPB), facilitating conditions (adapted from the MPCU) and compatibility (taken from the IDT) (Venkatesh et al., 2003: 453).

Encapsulated in the TPB, D-TPB and C-TAM-TPB, perceived behavioural control can be defined as the perceived ease or difficulty in performing a specific behaviour (Ajzen, 1991: 188). It includes the perception of an individual's abilities and sense of control over the situation and, according to Ham et al. (2015: 740), is defined as a combination of locus of control and self-efficacy. Locus of control refers to "… an individual's personal belief that the events which occur in life are either a result of personal control and effort, or outside factors such as fate or luck" (Van Niekerk, 2012: 20). Self-efficacy signifies an individual's internal belief in their own abilities and capabilities to perform a specific activity or action (Hu & Zhang, 2016: 645; Yul, 2014: 12). Therefore, perceived behavioural control refers to the availability of resources and opportunities for a particular behaviour to be performed and is influenced by factors such as previous experiences, convenience perceptions and monetary and time barriers which increase or decrease the perceived level of feasibility of this behaviour (Ham et al., 2015: 741).

A behaviour cannot occur when objective conditions in the environment prevent it; facilitating conditions therefore refer to the objective factors in the environment that make an act easy to do (Triandis, 1980 in Thompson et al., 1991: 129). For instance, returning items that were purchased online is simplified when no fee is charged to return them. In the context of the MPCU, Thompson et al. (1991: 129) explain that the provision of support for users of PCs may be one type of facilitating condition that can influence system utilisation.

Derived from the IDT, compatibility refers to "… the degree to which an innovation is perceived as difficult to understand and use" (Rogers, 1962: 15). Rogers (1962: 231) claims that while some innovations are clear in their meaning and readily understood by individuals of a social system, others are more complicated and will be adopted more slowly.

Venkatesh et al. (2003: 453) report significant empirical relationships between each of the sub-constructs (perceived behavioural control, facilitating conditions and complexity) and behavioural intention. Each of these sub-constructs is operationalised to include aspects of the technological and/or organisational environment that are intended to eliminate obstacles. Taylor and Todd (1995: 562) confirm the theoretical overlap by modelling facilitating conditions as a core component of perceived behavioural control in the TPB and the D-TPB. The compatibility construct, taken from the IDT, embodies items that explore the fit between an individual's work style and the use of a system in the organisation (Venkatesh et al., 2003: 453).

In conjunction with the eight technology acceptance theories utilised in the development of the UTAUT Model, Venkatesh et al. (2003: 427) postulate four key moderators that have been found to be significant: experience, voluntariness, gender and age. These four moderators will be discussed in the next section.

3.3.1.5 Moderators of the UTAUT Model

Quite often, researchers merely consider the direct influence of the independent constructs on the dependent construct, while discarding the impact of the moderator(s) on the particular relationship or correlation (Trojanowski & Kutak, 2017: 97-98). Trojanowski and Kutak (2017: 97-98) argue that individuals are likely to differ significantly from each other in terms of their beliefs, values, perceptions or their understanding of different constructs. Failure to examine the impact of heterogeneity may result in drawing incorrect conclusions and formulating invalid recommendations (Hair et al., 2012: 427; Trojanowski & Kutak, 2017: 97-98). Therefore, it is important to explore the interaction effect of moderators on the relationship between independent and dependent constructs.

In developing the UTAUT Model, Venkatesh et al. (2003: 427) explored the moderators as suggested by past technology acceptance theories. From a theoretical point of view, Venkatesh et al. (2003: 447-455) justified the inclusion of four moderators, namely experience, voluntariness of use, gender and age. The empirical analysis confirmed the significant moderating influence of experience, the voluntariness of use, gender and age as fundamental features of the UTAUT Model (Venkatesh et al., 2003: 467).

Performance expectancy appears to be a determinant of behavioural intention in most situations: the strength of the relationship varies with age and gender, such that it is more significant for men and younger workers. The influence of effort expectancy on behavioural intention is also moderated by age and gender. Effort expectancy was found to be more significant for women and older workers, and the influence decreases as their experience with the technology increases. The effect of social influence on behavioural intention is dependent on all four moderating variables. Lastly, the influence of facilitating conditions on actual usage was significant only when examined in conjunction with the moderating effects of age and experience. Facilitating conditions only matter to older workers in later stages of experience (Venkatesh et al., 2003: 467).

Table 3.2 categorises the role each of the four identified moderators played in the eight technology acceptance theories Venkatesh et al. (2003: 433) utilised in the development of the UTAUT Model.

Table 3.2: The role of moderators in eight existing technology acceptance models

	Moderators			
Model/theory	**Experience**	**Voluntariness**	**Gender**	**Age**
Theory of Reasoned Action (TRA)	Although not explicitly included, the role of experience was empirically examined using a cross-sectional analysis by Davis (1989).	Not included in the original TRA. However, research proposed that subjective norms were more significant when system use was perceived to be less voluntary.	N/A	N/A
Technology Acceptance Model (TAM) (and TAM2)	Not explicitly included in TAM. Davis et al. (1989) have provided empirical evidence showing that ease of use becomes non-significant with increased experience.	Not explicitly included in the original TAM. Within TAM2, subjective norm was salient only in mandatory settings and even then, only cases of limited experience with the system.	Not included in the original TAM. Empirical evidence demonstrated that perceived usefulness was more salient for men, whereas perceived ease of use was more salient for women. The effect of subjective norms was more salient for women in the early stages of experience.	N/A
Theory of Planned Behaviour (TPB)	Not explicitly included in the original TPB. Empirical evidence demonstrates that experience moderates the relationship between subjective norms and behavioural intent. Subjective norms become less significant with increasing levels of experience.	Not included in the original TPB. It is suggested that subjective norms are more significant when system use is perceived to be less voluntary.	Attitude was found to be more salient for men. Both subjective norms and perceived behavioural control were more salient for women in the early stages of experience.	Attitude was more salient for younger workers, whereas perceived behavioural control was more salient for older workers. Subjective norms were more salient for older women.
Model of PC Utilisation (MPCU)	Research has shown that complexity, affect towards use, social factors and facilitating conditions are more significant with less experience.	N/A	N/A	N/A

	Moderators			
Model/theory	**Experience**	**Voluntariness**	**Gender**	**Age**
Combined TAM and TPB (C-TAM-TPB)	Experience was incorporated in a between-subjects design (experienced and inexperienced users). Perceived usefulness, attitude towards behaviour and perceived behavioural control were more salient with increasing experience, whereas subjective norm became less salient with increasing experience.	N/A	N/A	N/A
Innovation Diffusion Theory (IDT)	Research indicates that the significant predictors for adoption are relative advantage, ease of use, trialability, result demonstrability and visibility.	Although not tested as a moderating variable, voluntariness was shown to have a direct effect on behavioural intention.	N/A	N/A
Motivational Model (MM)	N/A	N/A	N/A	N/A
Social Cognitive Theory (SCT)	N/A	N/A	N/A	N/A

Source: Taken and summarised from Venkatesh et al. (2003: 433-435)

3.3.2 SUMMARY

Empirical analyses provided strong support for the UTAUT Model, which postulates three direct determinants of behavioural intention to use a technology or system (performance expectancy effort expectancy and social influence) and two direct determinants of use behaviour (facilitating conditions and behavioural intention) (Venkatesh et al., 2003: 467). Substantial moderating effects of age, gender, experience and voluntariness of use on behavioural intention and use behaviour were confirmed as fundamental features of the UTAUT Model. The UTAUT Model accounts for 56% of the variance in behavioural intention and 40% variance in technology use, which is a substantial improvement over any of the initial eight technology acceptance theories used in the development of the UTAUT Model.

The UTAUT Model has successfully integrated key elements from 32 constructs, taken from eight existing technology acceptance theories, into a unified model posited by four main effects and four moderators (Venkatesh et al., 2003: 467). The four core constructs, as used in the UTAUT Model and discussed in section 3.3.1 above, are outlined and defined in Table 3.3. The root source of the construct from which it was derived is also provided.

Table 3.3: Constructs of UTAUT and the root source of the constructs

Constructs	Definition	Root source of the construct from earlier models/theories
Performance expectancy	"… the degree to which an individual believes that using the system will help him/her attain gains in job performance"	Constructs from existing models that capture the concept of performance expectancy include: • Perceived usefulness (TAM) • Extrinsic motivations (MM) • Job-fit (MPCU) • Relative advantage (IDT) • Outcome expectancy (SCT)
Effort expectancy	"… the degree of ease that can be associated with the use of a specific system"	Constructs pertaining to effort expectancy include: • Perceived ease of use (TAM) • Complexity (MPCU) • Ease of use (IDT)
Social influence	"… the extent to which an individual perceives that important others, such as family, friends or colleagues, believe they should use a particular technology system"	Three constructs related to social influence include: • Subjective norms (TRA, TAM, D-TPB, TPB) • Social factors (MPCU) • Image (IDT)

Constructs	Definition	Root source of the construct from earlier models/theories
Facilitating conditions	"… the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system"	Three constructs were used from earlier models: • Perceived behavioural control (TPB, D-TPB, C-TAM-TPB) • Facilitating conditions (MPCU) • Compatibility (IDT)

Source: Taken and summarised from Venkatesh et al. (2003: 450, 453); Venkatesh et al. (2012: 159)

Although the structural model was tested on all the scale items taken from the eight technology acceptance models, the sample posed a limitation due to the number of latent variables and associated items (Venkatesh et al., 2003: 457). Therefore, the data were re-analysed using only four of the highest-loading items from the measurement model for each of the constructs. The actual scale items used to validate the UTAUT Model are listed in Table 3.4.

Table 3.4: Scale items used in estimating the UTAUT Model

Construct	Scale items	
Performance expectancy	U6	I would find the system useful in my job.
	RA1	Using the system enables me to accomplish tasks more quickly.
	RA5	Using the system increases my productivity.
	OE7	If I use the system, I will increase my chances of getting a raise.
Effort expectancy	EOU3	My interaction with the system would be clear and understandable.
	EOU5	It would be easy for me to become skilful at using the system.
	EOU6	I would find the system easy to use.
	EU4	Learning to operate the system is easy for me.
Social influence	SN1	People who influence my behaviour think that I should use the system.
	SN2	People who are important to me think that I should use the system.
	SF2	The senior management of this business has been helpful in the use of the system.
	SF4	In general, the organisation has supported the use of the system.
Facilitating conditions	PBC2	I have the resources necessary to use the system.
	PBC3	I have the knowledge necessary to use the system.
	PBC5	The system is not compatible with other systems I use.
	FC3	A specific person (or group) is available for assistance with system difficulty.
Attitude towards using technology[#]	A1	Using the system is a bad/good idea.
	AF1	The system makes work more interesting.
	AF2	Working with the system is fun.
	Affect1	I like working with the system.
Self-efficacy[#]	I would complete a job or task using the system if …	
	SE1	there was no one around to tell me what to do as I go.
	SE4	I could call someone for help if I got stuck.
	SE6	I had a lot of time to complete the job for which the software was provided.
	SE7	I had just the built-in help facility for assistance.

Construct	Scale items	
Anxiety#	ANX1	I feel apprehensive about using the system.
	ANX2	It scares me to think that I could lose a lot of information using the system by hitting the wrong key.
	ANX3	I hesitate to use the system for fear of making mistakes I cannot correct.
	ANX4	The system is somewhat intimidating to me.
Behavioural intention to use the system	BI1	I intend to use the system in the next <n> months.
	BI2	I predict I would use the system in the next <n> months.
	BI3	I plan to use the system in the next <n> months.

Notes: # Construct removed by Venkatesh et al. (2003: 447). Refer to section 3.3.

Source: Venkatesh et al. (2003: 460)

Since its original publication in 2003, the UTAUT Model has served as the foundational theory in numerous technology acceptance and adoption studies and has been applied to a variety of organisational and non-organisational settings. The UTAUT Model in its entirety or only parts of the model have been applied and reapplied in organisational settings that have contributed to forfeiting the generalisability of the model. Venkatesh et al. (2012: 158) emphasise that the application, reapplication and extension or integration of the original UTAUT Model have been valuable in expanding researchers' understanding of technology acceptance and adoption behaviours and thereby extended the theoretical boundaries of the model.

However, in Venkatesh et al.'s review (2012: 158) of the vast number of research undertakings utilising the UTAUT Model, they found that most studies using UTAUT employed only a subset of the constructs, particularly by eliminating the moderators. Therefore, while most studies contribute to understanding the usefulness of the UTAUT Model in diverse contexts, there was still a need for a methodical analysis and theorising of the salient factors that would apply to the context of consumers' technology usage behaviours (Venkatesh et al., 2012: 158). Consequently, Venkatesh et al. (2012: 158) built on past extensions of the UTAUT Model by paying specific attention to the consumer usage context and developed the UTAUT2 Model. While the originally published UTAUT Model focused on determining technology adoption and usage behaviour by employees, the UTAUT2 Model was specifically introduced to investigate consumers' intention to accept and use innovative technologies (Gupta & Dogra, 2017: 147; Miladinovic & Xiang, 2016: 16). The development of the UTAUT2 Model will be explained in the next section.

3.4 THE UTAUT2 MODEL

In 2012, Venkatesh et al. (2012) modified and published an extended UTAUT Model after an extensive review of critique and the assessment of numerous research studies based on the original UTAUT Model. While the former UTAUT Model focused on determining technology adoption and usage behaviour by employees and in an organisational context, the UTAUT2 Model was specifically introduced to investigate consumer technologies and explain consumers' acceptance and adoption behaviours in particular (Gupta & Dogra, 2017: 147; Miladinovic & Xiang, 2016: 16). Venkatesh et al. (2012: 158) tailored the UTAUT Model to a consumer use context by identifying three additional key constructs from prior research on both technology adoption and use, altering existing relationships in the original conceptualisation of the UTAUT Model and introducing new relationships.

The extended UTAUT2 Model comprises the same four constructs as identified and validated in the original UTAUT Model, namely performance expectancy, effort expectancy, social influence and facilitating conditions, albeit differently applied and moderated (Goulão, 2014: 6). The UTAUT2 Model incorporates three additional constructs significant to the study of acceptance and use of technology in a consumer context, namely hedonic motivation, price value and habit (Venkatesh et al., 2012: 157). The relationship between facilitating conditions, hedonic motivations, price value as well as habit and behavioural intention is hypothesised to be moderated by age, gender and experience. The moderating variable (voluntariness of use) was excluded since consumers' behaviours are voluntary and they are not obligated to use the technology in question (Goulão, 2014: 6).

The UTAUT2 Model, as presented by Venkatesh et al. (2012: 160), is shown in Figure 3.2.

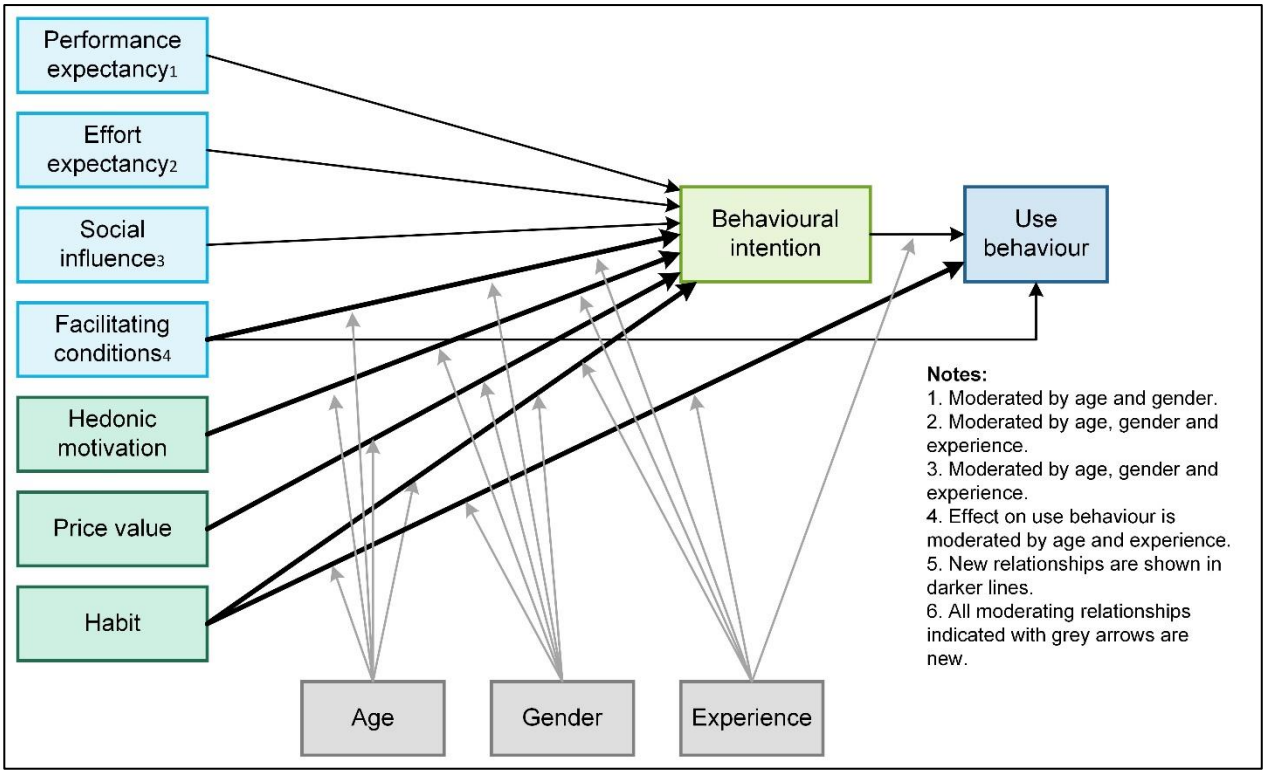

Figure 3.2: The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) Model
Source: Venkatesh et al. (2012: 160)

Information technology research has theorised and found numerous constructs related to hedonic motivation, which is significant in consumer product and/or technology use. By integrating hedonic motivation, the UTAUT's strongest predictor that emphasises utility was complemented. Furthermore, unlike in an organisational context, users are responsible for any costs, which can direct consumers' adoption behaviour. Venkatesh et al. (2012: 158) argue that the additional price value construct will supplement the UTAUT Model's existing resource considerations, which only focused on time and effort. Lastly, Venkatesh et al. (2012: 158) incorporated habit into the UTAUT2 Model to complement the theory's focus on intentionality as the overarching mechanism and key driver of behaviour. The additional three constructs as well as the three moderators incorporated in the UTAUT2 Model will be conceptualised in the next section.

3.4.1 INCLUSION OF ADDITIONAL CONSTRUCTS IN THE UTAUT2 MODEL

Apart from the formerly validated constructs identified in the UTAUT Model (performance expectancy, effort expectancy, social influence and facilitating conditions), Venkatesh et al. (2012: 160) identified and theorised the inclusion of three additional constructs in establishing technology adoption and use from a consumer's perspective. These additional constructs are hedonic motivations, price value and habit, and will be discussed below.

3.4.1.1 Hedonic motivations

Hedonic motivations refer to "… the fun or pleasure derived from using a technology" (Venkatesh et al. 2012: 161). Hedonic motivation – conceptualised as perceived enjoyment – has been proven to play a vital role in determining technology acceptance and usage behaviour in information systems research (Brown & Venkatesh, 2005: 406; Thong, Hong & Tam, 2006: 807; Uitz & Koitz, 2013: 130; Venkatesh et al., 2012: 161). It is argued that if the use of technology is gratifying, individuals can gain enjoyment, which influences their behavioural intention to pursue the technology (Lee, 2009: 852).

Since the publication of the UTAUT2 Model, multiple studies have examined the effect of hedonic motivation on users' behavioural intention and found it has a significant effect on the use of technology (e.g. Escobar-Rodríguez & Carvajar-Trujillo, 2014: 84; Hew et al., 2015: 1269; Miladinovic & Xiang, 2016: 50; To, Liao & Lin, 2007: 774). Tak and Panwar (2017: 252) cite that since emotions, derived from fun, pleasure and enjoyment, are involved in the acceptance of technology systems, hedonic motivation is a strong predictor of adoption. This was also proven by Huang and Kao (2015: 16), who found that hedonic motivation is the most significant dimension in light of the influence relationship. It can be inferred that the intention to use, or continue using, a specific technological device or system will increase the more users find it to be enjoyable (Miladinovic & Xiang, 2016: 50).

3.4.1.2 Price value

A vital difference between consumers' technology usage and organisational usage is that consumers generally bear the monetary cost of such usage, whereas employees do not. The cost and pricing structure of using the technology may have a significant impact on consumers' intentions to use a specific technology. Venkatesh et al. (2012: 161) consequently added price value as a predictor of behavioural intention to use technology from a consumer's perspective.

Price value is defined as "… consumers' cognitive trade-offs between the perceived benefits of the applications and the monetary costs for using them" (Venkatesh et al., 2012: 161). Venkatesh et al. (2012: 160) claim that technology is not offered free to a consumer by an organisation, and the cost of using the technology and the pricing structure has a substantial influence on consumers' technology use. According to Venkatesh et al. (2012: 161), price value follows the idea of perceived value, which entails also evaluating and comparing the perceptions of relative rewards received and the associated sacrifices paid. If perceived benefits outweigh the monetary

sacrifices paid for technology applications, this could influence technology usage (Venkatesh et al., 2012:161). According to Alwahaishi and Snášel (2013:64), the price value is positive when the perceived benefits of utilising technology outweigh the monetary costs, and such a price value has a favourable impact on intention. Miladinovic and Xiang (2016: 23) furthermore state that the price value can be positive or negative, depending on whether the perceived benefits exceed the monetary costs of using the specific technology.

3.4.1.3 Habit

Finally, Venkatesh et al. (2012: 161) incorporated habit into the UTAUT2 Model. Habit can be described as the degree to which individuals tend to perform a specific behaviour, or use specific technologies automatically, because of learning, and because of previous experiences (Hew et al., 2015: 1273; Venkatesh et al., 2012: 161). Habit has been operationalised in two distinct ways. Firstly, habit is measured as past experiences or behaviours that are learnt, and secondly, habit is denoted as the extent to which an individual believes the behaviour to be automatic (Kim & Malhotra, 2005: 752; Limayem et al., 2007: 705; Venkatesh et al., 2012: 161).

Habit has been considered in various studies as a predictor of technology usage intention (Hew et al., 2015: 1285; Limayem et al., 2007: 705) and is considered to directly influence a person's usage or planned behaviour (Escobar-Rodríguez & Carvajal-Trujillo, 2014: 83). In Limayem et al.'s study (2007: 705), a moderate effect was found between habit and behavioural intention; however, a strong relationship was found between habit and usage or planned behaviour. The moderate relationship between habit and behavioural intention could be because the intention to use specific technological systems will become less significant as the habit becomes stronger (Escobar-Rodríguez & Carvajal-Trujillo, 2014: 83). Hew et al. (2015: 1285) maintains that habit is a significant driver of intention to use technology because various technological systems are used by individuals daily, which make people unconsciously dependent on certain technological devices or systems.

The three additional constructs introduced by Venkatesh et al. (2012: 160-161) in the UTAUT2 Model are summarised and defined in Table 3.5.

Table 3.5: Additional constructs of the UTAUT2 Model

Construct	Definition
Hedonic motivation	"… the fun or pleasure derived from using a technology. Hedonic motivation is also conceptualised as perceived enjoyment"
Price value	"… consumers' cognitive trade-off between the perceived benefits of the applications and the monetary cost of using them"
Habit	"… the extent to which people tend to perform behaviours automatically because of learning" and is "… equated with automaticity"

Source: Venkatesh et al. (2012: 160-161)

The Likert scale items used in the validation of the UTAUT Model were adapted to the context of consumers' behavioural intention to use new technology and actual use. The scale items for the UTAUT constructs (performance expectancy, effort expectancy, social influence, facilitating conditions and behavioural intention) were adapted from Venkatesh et al. (2003: 460) to be relevant to a consumer context. The habit scale was taken and adapted from Limayem and Hirt (2003), the scale for hedonic motivation was adapted from Kim et al. (2005) and the price value scale was adapted from Dodds, Monroe and Grewal (1991) (in Venkatesh et al., 2012: 166). All scale items were measured using a 7-point Likert scale, ranging from strongly disagree (1) to strongly agree (5). The Likert scale items used in the validation of the UTAUT2 Model are listed in Table 3.6.

Table 3.6: UTAUT2 scale items

Construct	Scale items	
Performance expectancy	PE1	I would find mobile Internet useful in my daily life.
	PE2	Using mobile Internet increases my chances of achieving things that are important to me. (Item removed)
	PE3	Using mobile Internet helps me accomplish things more quickly.
	PE4	Using mobile Internet increases my productivity.
Effort expectancy	EE1	Learning how to use mobile Internet is easy for me.
	EE2	My interaction with mobile Internet is clear and understandable.
	EE3	I find mobile Internet easy to use.
	EE4	It is easy for me to become skilful at using mobile Internet.
Social influence	SI1	People who are important to me think that I should use mobile Internet.
	SI2	People who influence my behaviour think that I should use mobile Internet.
	SI3	People whose opinions I value prefer that I use mobile Internet.
Facilitating conditions	FC1	I have the resources necessary to use mobile Internet.
	FC2	I have the knowledge necessary to use mobile Internet.
	FC3	Mobile Internet is compatible with other technologies I use.
	FC4	I can get help from others when I have difficulties in using mobile Internet.

Construct	Scale items	
Hedonic motivation	HM1	Using mobile Internet is fun.
	HM2	Using mobile Internet is enjoyable.
	HM3	Using mobile Internet is very entertaining.
Price value	PV1	Mobile Internet is reasonably priced.
	PV2	Mobile Internet is a good value for the money.
	PV3	At the current price, mobile Internet provides a good value.
Habit	HT1	The use of mobile Internet has become a habit for me.
	HT2	I am addicted to using mobile Internet.
	HT3	I must use mobile Internet.
	HT4	Using mobile Internet has become natural to me. (Item removed)
Behavioural intention to use the system	BI1	I intend to continue using mobile Internet in the future.
	BI2	I will always try to use mobile Internet in my daily life.
	BI3	I plan to continue to use mobile Internet frequently.

Source: Venkatesh et al. (2012: 178)

The moderators included in the UTAUT2 Model will be explained in the next section.

3.4.1.4 Moderators of the UTAUT2 Model

Venkatesh et al. (2012: 171) further delineate how various individual characteristics, namely age, gender and experience, moderate the effect of hedonic motivation, price value and habit on behavioural intention. The fourth moderator, the voluntariness of use, as originally operationalised in the UTAUT Model was removed from the UTAUT2 Model. The omission of the moderator was necessary in a consumer context, as voluntariness can be regarded as a continuum from mandatory to voluntary. Consumers have no organisational mandate, and thus consumers' behaviours are completely voluntary (Venkatesh et al., 2012: 159).

Empirical analyses of the modified UTAUT2 Model revealed that the influence of hedonic motivation on behavioural intention was stronger for younger men with less technology experience, and the effect of price value was stronger for older women. Thus, the addition of hedonic motivation, price value and their interactions with the moderators was vital in expanding the scope and generalisability of UTAUT to the consumer environment (Venkatesh et al., 2012: 171). Hypotheses were developed with regard to the moderating effect of age, gender and experience on the habit of technology use based on the underlying process of habit activation and enforcement. The results indicated that older men with extensive usage experience tend to rely more on habit to drive technology use (Venkatesh et al., 2012: 172).

The UTAUT2 Model has been applied in several contexts and its hypothetical relationships are empirically proven and extensively supported by various researchers (e.g. Baptista & Oliveira, 2015; Chong & Ngai, 2013; Escobar-Rodríguez & Carvajal-Trujillo, 2014; Gupta & Dogra, 2017; Nair et al., 2015).

The significance of the UTAUT2 constructs in prior research will be discussed in depth in Chapter 4.

3.4.2 SUMMARY OF FINDINGS (UTAUT2)

The major theoretical contribution of the UTAUT2 Model was to modify the originally validated UTAUT Model for the consumer technology acceptance and use context. By doing so, Venkatesh et al. (2012: 171) extended the generalisability of the UTAUT Model from an organisational context to a consumer context. The UTAUT2 not only incorporated the main relationships from the UTAUT Model but also included new constructs (namely hedonic motivation, price value and habit) and relationships that extended the applicability of the UTAUT Model. Venkatesh et al. (2012: 172) used a two-stage online survey of 1 512 mobile Internet users to provide empirical support for the applicability of UTAUT2 to the consumer context.

Hedonic motivation was found to be a vital determinant of behavioural intention and a more significant driver of behaviour intent than performance expectancy in a non-organisational context. The findings reveal that price value was an important determinant in consumer decision-making regarding technology use and the moderating effects of the consumers' demographic profile that is rooted in mechanisms related to social roles. While the influence of facilitating conditions in an organisational context revealed only a direct effect on actual usage behaviour, in a consumer context, facilitating conditions also influence behavioural intention (Venkatesh et al., 2012: 172). Empirical evidence also supports the original UTAUT Model with the remaining constructs performing as expected in the consumer context. The effects of effort expectancy, performance expectancy and social influence on behavioural intention were all moderated by individual characteristics. A notable difference between the findings of the UTAUT and the UTAUT2 was the effect of behavioural intention on technology use. While behavioural intention had a positive effect on use in the UTAUT Model, the effect was moderated by experience with the target technology in the UTAUT2 Model (Venkatesh et al., 2012: 172).

The internal consistency reliabilities of multi-item scales modelled with reflective indicators were 0.75 or greater, signifying that the scales were reliable (Venkatesh et al., 2012: 167). The average

variance extracted (AVE) was larger than 0.70 in all cases and greater than the square of the correlations, thus indicating discriminant validity. Internal consistency and discriminant validity were furthermore supported by the pattern of loadings and cross-loadings, except for one performance expectancy item and one habit item being removed due to the low loadings. Technology use, which was modelled using six formative indicators, had weights between 0.26 and 0.40 (Venkatesh et al., 2012: 167). The variance explained in both behavioural intention (74%) and technology use (52%) is substantial, compared to the baseline UTAUT Model that explained 56% variance in behavioural intention and 40% variance in technology use.

The moderating effect of age, gender and experience on behavioural intention was furthermore explored. The hypotheses pertaining to the moderating effects between the independent variables and behavioural intention, and the findings, are summarised in Table 3.7.

Table 3.7: Empirical results of the hypotheses in validating the UTAUT2 Model

Hypothesis	Empirical findings
H_1: Age, gender and experience will moderate the effect of facilitating conditions on behavioural intention, such that the effect will be stronger among older women in early stages of experience with a technology.	Partially supported. Only gender and age were significant moderators. Experience was not a significant moderator.
H_2: Age, gender and experience will moderate the effect of hedonic motivation on behavioural intention, such that the effect will be stronger among younger men in early stages of experience with a technology.	Accepted
H_3: Age and gender will moderate the effect of price value on behavioural intention, such that the effect will be stronger among women, particularly older women.	Accepted
$H_{4(a)}$: Age, gender and experience will moderate the effect of habit on behavioural intention, such that the effect will be stronger for older men with high levels of experience with the technology.	Accepted
$H_{4(b)}$: Age, gender and experience will moderate the effect of habit on technology use, such that the effect will be stronger for older men with high levels of experience with the technology.	Accepted
H_5: Experience will moderate the effect of behavioural intention on use, such that the effect will be stronger for consumers with less experience.	Accepted

Source: Summarised from Venkatesh et al. (2012: 171)

The UTAUT2 Model provides empirical support for the applicability of the model in the consumer context and its suitability, validity and reliability to explain technology adoption in various contexts have been supported by numerous researchers (e.g. Al-Shafi, Weerakkody & Janssen, 2009; Bühler & Bick, 2013; Chang, Hwang, Hung & Li, 2007; El-Gayar & Moran, 2007; Gruzd et al., 2012; Hew et al., 2015; Tak & Panwar, 2017; Tan et al., 2017).

The UTAUT2 is a complex model with many constructs and is therefore not perceived to be trivial, limited in explanatory and predictive power, or to have questionable empirical value or lacking any practical value (Trojanowski & Kutak, 2017: 95). It can be concluded that the UTAUT2 Model has better explanatory power than the UTAUT Model (Gharaibeh & Arshad, 2018: 125) and is proven to be more robust in assessing and predicting behavioural intention and actual behaviour in a consumer context (Dwivedi et al., 2017: 719; Moghavvemi et al., 2013: 247; Taiwo & Downe, 2013: 48).

The quality of the UTAUT2 Model as a theory, according to Weber's framework and criteria for evaluating a theory (2012), will be discussed in the next section, followed by the limitations that have been found regarding the UTAUT and UTAUT2 Models.

3.4.3 THEORETICAL ANALYSIS OF THE UTAUT2 MODEL

Weber's framework and criteria for evaluating a theory (2012) were applied by Tamilmani, Rana, Wamba and Dwivedi (2021: 16-17) to assess the UTAUT2 Model's key merits and major limitations. Weber's overall framework evaluates a theory's parts as well as the theory as a whole. The parts of a theory entail four dimensions, namely its constructs, the associations, states and events. The theory as a whole is evaluated based on five dimensions, namely the importance, novelty, parsimony, level and falsifiability of the principal theory (Venkatesh et al., 2016: 338). According to Weber (2012: 6), both forms of evaluation are significant in assessing the quality of a theory. Weber (2012: 6) proclaims that a model can be deemed a theory if the model presents high-quality parts and if the model as a whole is regarded as high quality.

Weber's framework and criteria for assessing a theory were evaluated to establish the rigour and robustness of the UTAUT2 Model in using it as the foundational theory in the research study. Table 3.8 summarises Weber's framework and theory evaluation of the parts of the UATUT2 as well as the UTAUT2 Model as a whole.

Table 3.8: Evaluation of the UTAUT2 Model: Applying Weber's evaluation criteria (2012)

Dimensions	Evaluation criteria	Evaluation of the UTAUT2 model
Evaluation of the *parts* of the UTAUT2 Model		
Constructs: An attribute in general of some class of things in its domain.	• Underlying inside-boundary class of things identified clearly • Inside-boundary attributes in general defined precisely	• Consumer users of technology have been identified as the inside-boundary class of things. • Twelve inside-boundary attributes in general, including nine constructs and three moderators, are precisely defined.
Associations: In a static setting, an association shows that the value of one construct somehow relates to the value of another construct.	• Inside-boundary associations are defined precisely • Compelling justification provided for associations	• Inside-boundary and higher-order moderation effects are hypothesised and precisely defined. • Compelling justifications for the associations are provided.
States: A theory should clearly and precisely state the space of things in the class or classes of things that it is intended to cover.	• Inside-boundary states specified clearly • Outside-boundary states specified clearly	Although the inside-boundary and outside-boundary states are not explicitly stated, new constructs such as hedonic motivation, price value and habit are incorporated. Voluntariness of use as a moderator is omitted which emphasises that the theory focuses on consumers as a general state of space.
Events: An event of a thing is a change from one of its states to another of its states.	• Inside-boundary events specified clearly • Outside-boundary events specified clearly	As the UTAUT2 is essentially a static theory, it does not specify the inside- and outside-boundary events.
Evaluation of the UTAUT2 Model as *a whole*		
Importance or utility: The importance or utility of a theory is often assessed via judgements made about the importance of its focal phenomenon. The focal phenomenon might be deemed important from a research or practical viewpoint.	• Importance to practice • Importance to research	• The focus on consumer usage is of greater importance to practice with the burgeoning consumer technology industry. • 868 citations within five years underscores the focal phenomenon's degree of importance to researchers.
Novelty: The extent to which a theory is novel refers to the value ascribed to it by researchers and the likelihood that research ascribing the theory will be accepted for publication.	• New focal phenomena • New ways to conceive existing focal phenomena • New and important changes to an existing theory:	• The novelty lies mainly in conceiving the existing focal phenomenon of individual technology acceptance in a new context (consumers). In doing so, it contributes to existing theories: o It omits voluntariness of use as a moderator since consumer use of technology is voluntary.

Dimensions	Evaluation criteria	Evaluation of the UTAUT2 model
	○ Adding/deleting constructs and/or associations ○ Defining constructs and associations more precisely ○ Specifying the boundary of the theory more precisely	○ It adds three new constructs pertaining to consumers' use of technology. ○ It precisely defines the association among the constructs through its robust hypotheses. ○ It precisely specifies the boundary of the theory as a new focal phenomenon.
Parsimony: High-quality theories are parsimonious in that they achieve a high level of predictive and explanatory power in relation to their focal phenomena using a small number of constructs and associations.	Achieving a good level of explanatory power in relation to focal phenomena using a relatively small number of constructs and associations.	Although UTAUT2 has achieved higher explanatory power for both behavioural intention and usage behaviour in comparison to the UTAUT, its level of parsimony is relatively low with the large number of associations implied by the higher-order moderation effects.
Level: Theories should be formulated at an appropriate level – whether it is too specific or too broad to be interesting and useful.	The theory should be formulated at an appropriate level (micro, meso or macro).	UTAUT2 is formulated as a micro-level theory with consumers as the focal phenomenon. However, given the broad related individual use of technology user classes, such as students and citizens, a higher-level formulation is also necessary.
Falsifiability: Theories cannot be empirically tested and support for theories grows when their powers of prediction and/or explanation remain robust across different tests of the theory. These tests can be used to examine conditions researchers believe are more likely to lead to the theory being falsified (failing the empirical test) rather than supported.	The theory should be articulated clearly so that it is subject to robust empirical tests.	The robust empirical examination of the UTAUT2 is testimony to its well-articulated focal phenomenon and parts of the theory.

Source: Tamilmani et al. (2021: 16-17); Venkatesh et al. (2016: 340-341); Weber (2012: 6-16)

From the theoretical evaluation in Table 3.8, it can be inferred that the UTAUT2 Model is a high-quality theory. It performs well in defining and articulating the focal class of things (constructs) and the associations (Venkatesh et al. 2016: 338). However, the states and events parts of the UTAUT2 Model perform less well due to the inadequacy of boundary conditions and high conceivable space (Tamilmani et al., 2021: 17). Furthermore, the UTAUT2 Model as a whole performs well in the importance, novelty and falsifiability dimensions. Its focus on the important phenomenon of technology acceptance and use among consumers, a burgeoning multibillion-dollar industry, underscores the importance of the theory. The introduction of emotional attributes and higher-order moderators balances a largely cognitive-based UTAUT2 Model and brings novelty to the theory, and it is subject to rigorous empirical validation (Tamilmani et al., 2021: 17).

Apart from the advantages of the UTAUT2 Model, the model as a whole poses two limitations, based on Weber's criteria: (1) it has relatively low parsimony due to the complex interactions among attributes and the higher-order moderators; and (2) the theory merely focuses on the individual users of technology and lacks higher-level formulation in the model (Tamilmani et al., 2017: 17; Venkatesh et al., 2016: 338). Nevertheless, the UTAUT2 Model has proven to be a high-quality theory on both parameters of theory evaluation – the parts of the theory and the theory as a whole. Further critique and limitations of the UTAUT and UTAUT2 Models, as debated in the literature, are explored in the next section.

3.4.4 CRITICISMS AND LIMITATIONS OF THE UTAUT AND UTAUT2 MODELS

Although the UTAUT and UTAUT2 Models were considered robust and valid in various contexts, researchers have critiqued the models and have identified some limitations.

One of the major shortcomings of the UTAUT Model is that it is only applicable when applied within an organisational context and is therefore insignificant in exploring consumers' adoption of technology (Venkatesh et al., 2012: 157). In response to the criticism, Venkatesh et al. (2012: 158) enhanced the model from a consumer's perspective by publishing the UTAUT2 Model. The UTAUT and UTAUT2 Models were furthermore criticised for overlooking culture as a key element in the adoption of new technology (Van Niekerk, 2020: 123). Im, Kim and Han (2008: 1-2) add that the UTAUT Model disregards two other crucial factors: the type of technology engaged with and perceived risk. The current research study therefore addresses the limitation by including perceived risk as a construct that theoretically influences consumers' behavioural intention to continue using same-day delivery apps (refer to Chapter 4, section 4.2.10).

Furthermore, based on well-established theories in information systems and social psychology research, it has been proven that behavioural intention mediates the influence of various beliefs and external constructs on behaviour and is thus an important predictor of behaviour (Moghavvemi et al., 2013: 247). However, the relationship between behavioural intention and actual behaviour is complex and requires more scrutiny, which has unveiled three limitations of the UTAUT Models (Waehama, McGrath, Korthaus & Fong, 2014: 5). Firstly, Moghavvemi et al. (2013: 247) argue that behavioural intention does not fully consider all possible external factors that can affect the performance of a behaviour. Thus, the role of external variables, such as social and monetary influences, which could potentially hinder or simplify the performance of a behaviour is not fully considered by behavioural intention. Secondly, Moghavvemi et al. (2013: 247) claim that behavioural intention has a weak predictive and explanatory ability to deal with ambiguity and unexpected events that may occur between the time the intention was formed, and the given behaviour was performed. Various internal and external stimuli can alter the temporary intention, rendering behavioural intention inaccurate, unstable and less predictive of actual behaviour. Sheeran and Webb (2016: 506) identify the gap between behavioural intention and actual behaviour as the intention-behaviour gap. Lastly, behavioural intention is ineffective in predicting behaviours that are not entirely within an individual's volitional control (Moghavvemi et al., 2013: 245).

To address the above limitations in terms of the relationship between intention and actual usage behaviour, researchers included 'precipitating occasions or events' as a moderator to measure the impact of external factors on the relationship between behavioural intention and actual usage (Moghavvemi et al., 2013: 245; Waehama et al., 2014: 5). The moderator, precipitating events, can be defined as certain exogenous variables that can serve to facilitate or precipitate the realisation of intention into behaviour (Moghavvemi et al., 2013: 249). The intention-behaviour gap was not addressed in the current research study as the purpose was to explore consumers' intention towards using same-day delivery apps. The research study furthermore supports and endorses the notion that intention to use culminates in actual use, as theorised by Ajzen (1991: 181) in the TPB and confirmed by various scholars (e.g. Hossain, Hasan, Chan & Ahmed, 2017: 15; Lewis et al., 2013: 30; Uphaus, Ehlers & Rau, 2019: 14; Yun et al., 2013: 222; Venkatesh et al., 2003: 468).

Moreover, the UTAUT Model, according to Dwivedi et al. (2017: 719), theorises relationships that may not be applicable to all contexts, it omits relationships that may potentially be important and it excludes constructs that may be significant for explaining technology acceptance and use. The UTAUT and UTAUT2 Models, for example, exclude self-efficacy and attitude as direct

determinants of behavioural intention (Ahmad, 2014: 3; Moghavvemi et al., 2013: 245). Self-efficacy has been shown to be conceptually and empirically distinct from effort expectancy and was therefore not considered significant in the UTAUT Model (Venkatesh et al., 2003: 455). Inexperienced users may view new technological systems or devices as complex, and confidence in their ability to use these new technologies has a significant influence on their acceptance (Lee & Hsieh, 2009: 1; Wang & Wang, 2008: 405; Yul, 2014: 12-13). Moghavvemi et al. (2013: 247) therefore argue that a higher level of self-efficacy will lead to an increased intention to use new technologies. Furthermore, Venkatesh et al. (2003: 455) omitted the attitudinal construct from the UTAUT Model as they argued that the construct was shown to be significant only when specific conditions (i.e. performance and effort expectancy) were not included in the model. The TPB, TRA and TAM have, however, considered attitude as a significant and direct determinant of behavioural intention. The current research study addresses these limitations by including perceived self-efficacy and the attitudinal construct as determinants that theoretically influence South African consumers' behavioural intention to continue using same-day delivery apps (refer to Chapter 4, sections 4.2.11 and 4.2.12).

Despite the shortcomings of the UTAUT2 Model, it continues to be applied in technology acceptance research (Van Niekerk, 2020: 123). The UTAUT2 Model has, nevertheless, been proven to be a rigorous model in establishing behavioural intention and use behaviour in a consumer context. According to Miladinovic and Xiang (2016: 19), the UTAUT2 Model outperforms all other technology acceptance theories and models. This is in line with Rondan-Cataluña et al. (2015: 598) as their research has proven that the UTAUT2 Model has 26% better explanatory power than other technology acceptance theories. The UTAUT2 Model further explains up to 74% of the variance in consumers' behavioural intention to use technology – a 4% increase from its predecessor (the UTAUT Model) (Hoque & Sorwar, 2017: 77; Martins, Oliveira & Popvič, 2014: 4; Slade, Williams & Dwivedi, 2013: 11).

3.5 CONCLUSION

Throughout the years, several theories have been developed and applied in a vast array of research studies in a technological context, as well as other areas of academic interest. These theories have proven their enhanced applicability in modelling technology acceptance in various contextual settings. To provide a unified model of technology acceptance and use model, seminal authors Venkatesh et al. (2003) developed and validated the UTAUT Model by integrating determinants across eight well-established technology acceptance theories. These theories are IDT, TRA, TPB, TAM, C-TAM-TPB, MPCU, MM as well as SCT. In 2012, Venkatesh et al. (2012)

modified and published the extended UTAUT2 Model. While the originally published UTAUT Model focused on determining technology adoption and use behaviour by employees and in an organisational context, the UTAUT2 Model was specifically introduced to investigate consumers' acceptance and adoption behaviours.

The purpose of Chapter 3 was to establish the scientific and methodological rigour of the UTAUT2 Model to position an improved theoretical paradigm for the purpose of the research study. After an extensive review of the literature on the UTAUT2 Model, assessing the UTAUT2 Model against Weber's framework and criteria for evaluating a theory (2012) and exploring the criticism and limitations of the model, it was concluded that the UTAUT2 Model provides a solid theoretical foundation to explain consumers' behavioural intention to adopt or reject new technology. The UTAUT2 Model was therefore used as the foundational framework for the current research study, which endeavoured to develop and empirically test a theoretically grounded model to provide retailers with a consolidated model synthesising the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps.

The following literature research objective was achieved in Chapter 3:

Research objective 2: To assess the scientific and methodological rigour of the UTAUT2 Model to position an improved theoretical paradigm to use the model as the foundational framework for the research study.

Chapter 4 will build on the UTAUT2 Model as the theoretical foundation by exploring salient factors that are significant in the development of an extended UTAUT2 Model. The most prominent constructs, identified from an extant literature review and pertinent to the behavioural intention to continue using same-day delivery apps, will be discussed. These constructs will be conceptualised and explained in the context of the research study, and the significance of the constructs in determining behavioural intention to continue using an information system or technological device will be explored. The proposed conceptual model for South African consumers' behavioural intention to continue using same-day delivery apps is presented.

CHAPTER 4:
THEORETICAL INTEGRATION, PROPOSED THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

4.1 INTRODUCTION

The theoretical validation for the proposed conceptual model, as presented in Chapter 1 (Figure 1.3), measuring consumers' behavioural intention to continue using same-day delivery apps, will be discussed in Chapter 4. Although the UTAUT2 Model underpins the conceptual model of the study, it cannot fully explain users' acceptance of same-day delivery apps without introducing certain modifications, such as new dimensions and relationships that better reflect the behaviours of users towards same-day delivery apps, especially in a South African context. Constructs identified from several scholarly works and empirically validated results will be addressed, which have proven to be key determinants in establishing consumers' behavioural intention in various cultural settings and contexts. These constructs will be conceptualised and explained in the context of the research study, and the significance of the constructs in establishing the behavioural intention of an information system or technological device will be investigated. Based on the comprehensive literature discussion, and hypotheses provided in this chapter, a theoretically integrated discussion of the identified constructs in a conceptual model for consumers' behavioural intention to continue using same-day delivery apps in South Africa will be provided.

4.2 THEORETICAL DIMENSIONS: TOWARDS A CONCEPTUAL MODEL FOR MEASURING CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

A conceptual model can be described as a representational illustration and an empirical device that visually portrays the concepts and theories under investigation. Conceptual models provide a common understanding of the current knowledge of the subject matter, by showing various elements of a system and its interrelationships (Elangovan & Rajendran, 2015: 2). The conceptual model proposed in the research study uses standard conventions to represent the causal, sequential and logical arguments found in the literature.

The UTAUT2 Model focuses on predictions that relate the characteristics of users' reactions to information systems or technology and their intentions that will impact their behaviours. Venkatesh

et al. (2016: 346) recommend that the main effects in the UTAUT2 Model serve as the baseline for future research studies for parsimony, in an attempt to achieve good levels of predictive and explanatory power in relation to the focal phenomena of the theory. As a starting point, the main effects of the UTAUT2 Model were used in the conceptual model as the foundation for measuring consumers' behavioural intention to continue using same-day delivery apps. The research study further built on the UTAUT2 Model by incorporating additional exogenous mechanisms or constructs identified from a comprehensive literature search (discussed in sections 4.2.2 to 4.2.12). An exogenous mechanism is a variable that is changed or determined by its relationship with other variables in the model and is synonymous with a dependent variable.

Metatheoretical analyses conducted by Venkatesh et al. (2016: 335) reveal that former scholarly work included mostly new exogenous mechanisms to the existing UTAUT2 Model. Extensions of the UTAUT2 Model have the most potential for making substantial theoretical contributions to information systems research on technology acceptance and use behaviours (Venkatesh et al., 2016: 338). However, in Venkatesh et al.'s review (2012: 158) of the vast number of research undertakings utilising the UTAUT2 Model, they found that most studies employed only a subset of the constructs, particularly by eliminating the moderating variables. Therefore, while many studies contribute to understanding the usefulness of the UTAUT2 in diverse contexts, there is still a need for a methodical analysis and theorising of the salient factors that would apply to the context of consumers' technology usage behaviours (Venkatesh et al., 2012: 158).

Seminal authors Venkatesh et al. (2003: 470) recommend that further empirical research initiatives be attempted to explore and assess the influence of various additional boundary conditions of the UTAUT2 Model, to provide a better understanding of technology adoption and use behaviour. Venkatesh et al. (2003: 470) further suggest that future studies might consider including additional theoretically motivated moderators, different technological systems or devices, various user groups, or other contexts and/or industries. For the purpose of the research study, the main effects of the UTAUT2 Model have been applied in the marketing and retailing industry (industry), focusing on same-day delivery apps (context) and incorporating new exogenous mechanisms to examine their significance in relation to behavioural intention. The research study furthermore included the moderating effect of two demographic variables on the interrelationship between the independent constructs and dependent construct (behavioural intention). The research study therefore not only contributes to the body of knowledge on behavioural intention research, but also offers a methodical analysis and theorising of salient factors that could be applied in the context of consumers' technology use behaviours.

A metatheoretical review of the extant literature provides theoretical justification affirming the inclusion of 11 independent constructs in exploring behavioural intention in a South African context: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. Moreover, due to the substantial contribution of demographic differences to technology adoption and/or acceptance behaviour research, it was deemed fit to include two moderating constructs. The moderating effect of generational cohort (i.e. age group) and gender on consumers' behavioural intention was included in the conceptual model to investigate demographic differences.

The theoretical basis for including and validating the 11 identified independent constructs is provided in the sections that follow. Given the current research study and context, the incorporation of the UTAUT2 Model's main effects and the new exogenous mechanisms acknowledged in the literature is justified. To substantiate the dependent construct's importance in the research study, the interrelationships between the various independent constructs and the dependent construct are investigated. First, the dependent construct of behavioural intention is explored.

4.2.1 DEPENDENT CONSTRUCT: BEHAVIOURAL INTENTION

To determine the feasibility and viability of the implementation of a new technological device or system, consumers' subsequent intention to use these new systems needs to be determined, which culminates in actual technology use (Erasmus, Rothmann & Van Eeden, 2015: 2). In the TPB, Ajzen (1991: 182) theorises that an individual's intention to perform a specific behaviour is the best predictor of whether the individual will perform that behaviour. Many technology adoption theories have suggested the impact of behavioural intention on use behaviour. However, the causal link is largely omitted in research because there are already numerous examples of empirical support for this relationship, and further investigation is considered extraneous (Venkatesh & Davis, 2000: 187; Yun et al., 2013: 220).

The scope of the research study was to identify salient factors that influence the continuance intention to use same-day delivery apps, and not to determine the causal link between behavioural intention and actual use behaviour. Continuance intention furthermore imply that consumers are already actively using same-day delivery apps.

Intentions have been defined in several seminal research studies, such as the SCT, the TRA and the TPB, as "… the amount of effort one is willing to exert to attain a goal" (Ajzen, 1991: 181), the "… behavioural plans that enable attainment of a behavioural goal" (Ajzen, 1996: 297), "… the degree of intensity of an individual's intention to perform a specific behaviour" (Fishbein & Azjen, 1975: 289), or simply as "proximal goals" (Bandura, 1998: 628). Behavioural intention is purely defined as "… a person's likelihood or subjective probability to engage in a given behaviour" (CHIRr, n.d.). Seminal author Icek Ajzen argues that behavioural intention reflects how hard a person is willing to try and how motivated they are to perform a given behaviour (Ajzen, 1991: 181). Intentions are assumed to capture the motivational factors that influence a behaviour and are indications of how much effort people are planning and willing to exert to perform the behaviour (Ajzen, 1991: 181). An effort was made through this research study to determine consumers' behavioural intention to continue using same-day delivery apps in a South African context.

Consumers' behavioural intention to continue using a technology refers to their willingness and determination to maintain their engagement with a particular technology over time. This concept goes beyond initial adoption and explores the factors that influence an individual's decision to persist in using a technology despite potential challenges or alternatives (Basak & Calisir, 2015: 181). Understanding the determinants of continuance intention is crucial for businesses and organisations that aim to foster long-term customer relationships and promote sustained technology adoption within their user base (Humbani & Wiese, 2019: 4).

The main effects from the UTAUT2 Model, which are incorporated in the conceptually developed model presented in Chapter 1 (see Figure 1.3), as well as the additional constructs identified from an extensive literature review as salient factors that could influence consumers' behaviour intention to continue using new technologies, will be discussed in the following sections. Existing literature provides support for the hypotheses developed for the research study. The formulation of these hypotheses led to the development of the theoretically grounded conceptual model illustrated later in this chapter. Each construct's inclusion is theoretically justified, and the hypotheses offered are supported by scholarly work. The first construct identified in the UTAUT2 Model is performance expectancy, which will be discussed next.

4.2.2 PERFORMANCE EXPECTANCY

Performance expectancy is one of the most important constructs of behavioural intention and has received considerable attention from researchers in a variety of fields (see Hamzat & Mabawonku, 2018: 3). The term 'performance expectancy' emerged from Venkatesh et al.'s UTAUT Model

(2003: 447), by combining five constructs from several different theories and models. ‘Perceived usefulness’ from the TAM was merged with ‘extrinsic motivation’ from the MM, ‘job-fit’ from the MPCU, ‘relative advantage’ from the IDT and ‘outcome expectations’ from the SCT (Venkatesh et al., 2003: 447). Venkatesh et al. (2003: 447) explain that these five constructs were merged due to their operational similarities and comparable measurement scales.

In the UTAUT2 Model, which focuses on adoption behaviours from a consumer’s perspective, performance expectancy is defined as “… the degree to which using a technology will provide benefits to consumers in performing certain activities” (Venkatesh et al., 2012: 159). Performance expectancy is consistent with the construct ‘perceived usefulness’ (Sair & Danish, 2018: 503), which denotes the degree to which a person believes that using a particular system would enhance their performance (Davis, 1989: 320). The literature suggests similarities between performance expectancy and perceived usefulness and confirms its worth in exploring consumers’ behavioural intention to adopt new technologies or devices (e.g. Escobar-Rodríguez & Carvajal-Trujillo, 2014: 70; Leong et al., 2013a: 2109; Leong, Hew, Tan & Ooi, 2013b: 5604; Madan & Yadav, 2016: 227; McKenna et al., 2014: 1; Miladinovic & Xiang, 2016: 1; Okumus & Bilgihan, 2014: 31; Palos-Sanchez, Hernandez-Mogollon & Campon-Cerro, 2017: 1; Roback & Wakefield, 2013: 19). It is argued that consumers are more inclined to keep using a technology that they find useful or that provides certain benefits.

In the context of the research study, performance expectancy refers to the degree to which an individual perceives that using same-day delivery apps would provide them with the benefits of performing specific activities in everyday situations (Huang & Kao, 2015: 5). Saving time and effort is one of the benefits of same-day delivery apps, which allow convenient shopping from anywhere, at any time. It might also suggest receiving a fast response because an individual only needs to open an app to get immediate access to what they are looking for. Mobile apps could furthermore allow users to accomplish personal goals successfully and efficiently (Van Niekerk, 2020: 137), such as having a concierge do the shopping while they attend to work, children or dinner. Another potential benefit that presented itself, especially during the COVID-19 pandemic, was having products delivered to an individual’s chosen location within a short period of time and not having to visit a brick-and-mortar store to purchase products.

To determine whether a consumer believes that using same-day delivery apps will give them certain benefits and whether these benefits will influence them to continue using same-day delivery apps, it was deemed appropriate to include the performance expectancy construct in the research study.

Performance expectancy is one of the factors in technology adoption research that has been examined the most, and it has been shown to be a significant predictor of behavioural intention to use a particular system or technology (e.g. Chao, 2019: 1; Chopdar & Sivakumar, 2019: 46; Hamzat & Mabawonku, 2018: 3; Hew et al., 2015: 1269; Park, Chung & Hur, 2011a: 1; Palau-Saumell, Forgas-Coll, Sánchez-García & Robres, 2019: 1; Sair & Danish, 2018: 501; Venkatesh et al., 2012: 160; Zhao & Bacao, 2020: 4). In the UTAUT2 Model, Venkatesh et al. (2012: 170) reported a substantial effect of performance expectancy on behavioural intention, and Nunes et al. (2019: 5) as well as Yuan, Ma, Kanthawala and Peng (2015: 735) found performance expectancy to be the only determinant to exert an influence on the behavioural intention to use mobile health apps. In their study, Hew et al. (2015: 1269) investigated the determinants of consumers' intention to continue using mobile apps and found performance expectancy to positively influence behavioural intention. Performance expectancy was furthermore reported to have a noteworthy influence on behavioural intention towards mobile learning (Chao, 2019: 1), mobile shopping apps (Chopdar & Sivakumar, 2019: 53), the use of mobile apps among university students (Fadzil, 2017: 1), the use of smartphones for learning by postgraduate students in Nigeria (Onaolapo & Oyewole, 2018: 110) and to purchase tourism-related products and services (Tan et al., 2017: 561), among others. Performance expectancy has been observed in numerous research undertakings to be a key driver of m-commerce acceptance behaviour (Baptista & Oliveira, 2015: 418; Chopdar & Sivakumar, 2019: 46; Sair & Danish, 2018: 501).

Two studies could be found that used the UTAUT Model to examine the use of same-day delivery apps or on-demand service delivery apps. Erwanti et al. (2018: 13) examined the factors influencing the continued use of a specific on-demand mobile app (GO-JEK) but found performance expectancy to be an insignificant predictor of intention. Yapp et al. (2018: 105) explored the factors that drive intention to adopt on-demand services among male and female technology users in Malaysia, but performance expectancy on intention was not supported.

Research pertaining to the significance of performance expectancy on the intention to continue using same-day delivery apps specifically was scant. The UTAUT Model was extended and applied by several researchers in examining the determinants that impact the adoption of on-demand or online food delivery services or apps (Erwanti et al., 2018: 13; Flores & Castaño, 2020: 25; Karulkar, Pahuja, Uppal & Sayed, 2019: 146; Lee et al., 2019: 1; Mensah, 2019: 23; Muangmee et al., 2021: 1297; Rasli et al., 2020: 679). Lee et al. (2019: 9) and Mensah (2019: 31) found performance expectancy to have the strongest positive effect on intention, whereas Karulkar et al. (2019: 158) reported performance expectancy to be the third most dominant variable in their study. Contradictory findings were reported by Rasli et al. (2020: 679), Erwanti et al. (2018: 13)

and Yapp et al. (2018: 118), as they found no significant relationship between performance expectancy and consumers' intention to use online food delivery apps or on-demand service delivery apps. In a more recent study, Zhao and Bacao (2020: 1) examined the factors that determined customers' continuing to use food delivery apps during the COVID-19 pandemic and concurred with previous research findings that performance expectancy has a statistically significant effect on continuance usage intentions. Lastly, in a South African study, Musakwa (2021: 48) qualitatively investigated customer experiences using a specific South African mobile delivery service app (Checkers Sixty60) and confirmed performance expectancy as a factor that influences user intention to use mobile delivery apps. The reviewers anticipated that using the same-day delivery app would help them with their purchasing needs. Due to the COVID-19 pandemic and related lockdown restrictions, users found the app useful because it spared them from having to go grocery shopping in crowded stores (Musakwa, 2021: 48).

From the extant literature review and prior empirical findings, the intention of the research study was to investigate whether performance expectancy has the same significant influence on consumers' behavioural intention to continue using same-day delivery apps; hence the following hypothesis:

Hypothesis 1: *There is a significant relationship between performance expectancy and consumers' behavioural intention to continue using same-day delivery apps.*

The second construct to be included from the UTAUT2 Model is effort expectancy, which will be discussed in the next section.

4.2.3 EFFORT EXPECTANCY

Effort expectancy emerged in the development of the UTAUT Model, which derived from three measures that are related to ease of use, namely perceived ease of use (taken from TAM), ease of use (taken from IDT) and the complexity in using the technology (taken from MPCU) (Venkatesh et al., 2003: 450). Similar to the performance expectancy construct discussed above, the aforementioned three constructs were merged into one single construct due to their resemblance to one another (Van Niekerk, 2020: 138).

Effort expectancy, as conceptualised by Venkatesh et al. (2003: 450; 2012: 159), refers to the degree of ease that can be associated with the use of a specific technology, device, or system. Effort expectancy represents the use of new technology, device, or service without additional

efforts from the user or without encountering much difficulty (Soni, Jain & Kumar, 2019: 363; Yun et al., 2013: 219). It is believed that using a new technology would be easy and convenient (Soni et al., 2019: 363) and therefore, Lee et al. (2019: 4) claim that a higher perception of ease of use leads to a higher intention to use the technology. When consumers believe that using new technology is free of any effort, their adoption of it will increase (Kang et al., 2015: 212).

Research further suggests that the more complex the technology or device, the lower its rate of adoption will be, especially among consumers (Venkatesh, Thong, Chan, Hu & Brown, 2011: 533). Shaw and Sergueeva (2016: 14) maintain that mobile apps are designed to be easy to use and are generally easily learnt. In an emerging economy such as South Africa, Van Niekerk (2020: 139) contends that the ease of using a mobile shopping app, such as same-day delivery apps, will be a motivating factor for consumers to adopt. In essence, the less the effort required by a consumer to use a mobile app, the easier its adoption will be. From an m-commerce perspective, effort expectancy refers to the ease of using a mobile touchscreen with an intuitive interface allowing users to operate the mobile app better and faster, and the efficiency of the mobile app (Van Niekerk, 2020: 139). Effort expectancy is therefore considered a measure of ease associated with using a mobile app (Kim & Baek, 2017: 151) and thus refers to the extent to which users believe that their continued use of same-day delivery apps will be free of any effort, easy to use, efficient, clear and understandable. Effort expectancy signifies how easily a consumer can use a same-day delivery app to shop for goods, make purchase decisions and conveniently receive ordered products on the same day.

Effort expectancy and its influence on behavioural intention have been explored in research relating to various types of mobile apps, shopping apps or delivery apps. Some researchers report that effort expectancy has an insignificant effect on the intention to use mobile technologies, such as on the adoption of food delivery apps (Flores & Castaño, 2020: 25; Lee et al., 2019: 9; Zhao & Bacao, 2020: 8), on-demand mobile service apps (Erwanti et al., 2018: 12; Yapp et al., 2018: 118) and mobile shopping apps (Chopdar & Sivakumar, 2019: 52; Van Niekerk, 2020: 270). This insignificant relationship between effort expectancy and behavioural intention could be attributed to users becoming increasingly more familiar with mobile technology and therefore little effort is required by consumers in their initial adoption of these mobile technologies (Zhao & Bacao, 2020: 4). Flores and Castaño (2020: 37) argue that the insignificance of effort expectancy on the adoption of food delivery apps in their study could be because consumers' purchasing behaviours are impacted by the convenience provided by the app rather than the technicality on how food delivery apps could be used effortlessly.

Contrary to the insignificant relationship findings reported above, several researchers report a noteworthy relationship between effort expectancy and behavioural intention (e.g. Alalwan et al., 2017: 99; Hew et al., 2015: 1269; Karulkar et al., 2019: 156; Rasli et al., 2020: 685; Venkatesh et al., 2011: 544). For example, Chopdar et al. (2018: 25) report a significant influence of effort expectancy on consumers' mobile shopping app adoption behaviour. A small but significant effect of effort expectancy on behavioural intention is reported by Shaw and Sergueeva (2016: 14), who explored the adoption of smartphones for m-commerce purposes. Soni et al. (2019: 369) and Tak and Panwar (2017: 12) arrived at the same conclusion, as their findings reveal a positive relationship between effort expectancy and behavioural intention to use mobile phones or apps for shopping. The literature related to on-demand or online food delivery services or apps, albeit limited, explored the determinants that impact consumers' behavioural intention to use online food delivery services/apps and coincides with previous research in finding that effort expectancy significantly influences behavioural intention (Karulkar et al., 2019: 146; Mensah, 2019: 32; Muangmee et al., 2021: 1306; Musakwa, 2021: iii; Rasli et al., 2020: 679).

Many researchers support the inclusion of effort expectancy in m-commerce and adoption behaviour research, emphasising the argument that effort expectancy has a positive influence on the behavioural intention of consumers to use m-commerce apps. Since effort expectancy is validated as having a positive effect on behavioural intention to adopt various m-commerce and mobile app innovations, its significance in the research study was investigated. Based on previous research findings, it was expected that effort expectancy would have a significant influence on consumers' behavioural intention and therefore the following hypothesis is formulated:

Hypothesis 2: *There is a significant relationship between effort expectancy and consumers' behavioural intention to continue using same-day delivery apps.*

The impact of facilitating conditions on behavioural intention, as identified in the UTAUT2 Model, will be discussed in the context of the research study in the following section.

4.2.4 FACILITATING CONDITIONS

Facilitating conditions represent a user's perception that the necessary resources and support are available to perform a given behaviour (Venkatesh et al., 2012: 159). It is an individual's belief that organisational and technical infrastructure exists to support the use of the technology (Venkatesh et al., 2003: 453). Derived from the UTAUT Model, the definition of facilitating conditions captures concepts embodied by three constructs from several existing theories, namely perceived

behavioural control taken from the TPB, D-TPB and the C-TAM-TPB, facilitating conditions taken from MPCU and compatibility taken from the IDT (Venkatesh et al., 2003: 453). Each of these constructs was operationalised to include aspects of the technological and/or organisational environment designed to remove barriers to use, and therefore the consolidation of these three constructs into one construct was defendable.

From a technological point of view, facilitating conditions refer to the degree to which a user believes that technical infrastructure and operational support exist to help users successfully use the system or device whenever necessary (Baptista & Olivera, 2015: 421; Ho & Amin, 2019: 27; Huang & Kao, 2015: 6). In the context of m-commerce, facilitating conditions represent "… a working, continuous Internet connection, a smartphone that is Internet-enabled and a working knowledge on the technology" (Van Niekerk, 2020: 142). Individuals generally look for assistance when they are experiencing the use of new technology and might refrain from using new technology when facilitating conditions are inadequate (Lewis et al., 2013: 25). Facilitating conditions are therefore the element that is solely available in the environment that has an impact on an individual's tendency to carry out a specific task (Rezaei et al., 2016: 417). Ho and Amin (2019: 27) state that the facilitating conditions in using mobile apps signify the mandatory technology resources, such as the memory of the mobile device, the speed of the Internet and the ability of the user in using the app. For the purpose of the research study, facilitating conditions are conceptualised as users' beliefs that the necessary services, resources and support are available to assist them in using same-day delivery apps successfully and continually.

Facilitating conditions have been widely reported by researchers to have a noteworthy influence on consumers' behavioural intention to use mobile shopping apps (Chopdar et al., 2018: 120; Miladinovic & Xiang, 2016: 50; Soni et al., 2019: 369; Verkijika, 2018: 1672), food delivery service apps (Karulkar et al., 2019: 159; Musakwa, 2021: iii) and on-demand service apps (Erwanti et al., 2018: 9; Yapp et al., 2018: 105). Miladinovic and Xiang (2016: 50) and Soni et al. (2019: 369) found that facilitating conditions positively impact users' behavioural intention to use fashion mobile shopping apps. In a comparative study on the acceptance and use of mobile shopping apps, Chopdar et al. (2018: 120) reveal that facilitating conditions had a significant influence on behavioural intention in both the USA and India. Verkijika (2018: 1672) concurs with these findings and reports a noteworthy relationship between facilitating conditions and behavioural intention to use m-commerce apps in Cameroon. Erwanti et al. (2018: 9) employed the UTAUT2 and DeLone and McLean's Information Systems Success Model and found that facilitating conditions significantly influence continuance intention to use a specific Indonesian on-demand mobile service (GO-JEK). In a similar study, Karulkar et al. (2019: 159) examined the adoption of online

food delivery apps by modifying the UTAUT Model and revealed that facilitating conditions were the second most dominant variable influencing individuals' adoption. In a comparative study, Yapp et al. (2018: 105) report that facilitating conditions had a significant effect on the adoption of on-demand services among female users, but not among male users. In a South African study exploring the factors that influence consumers' behavioural intention to use m-commerce apps to purchase athleisure apparel, no significant path between facilitating conditions and behavioural intention was found (Van Niekerk, 2020: 276). Facilitating conditions were also found to be insignificant in determining individuals' intention to use on-demand food delivery apps in Bangkok (Elango et al., 2019: 12), food delivery apps in Korea (Lee et al., 2019: 9), the Philippines (Flores & Castaño, 2020: 25) and Malaysia (Rasli et al., 2020: 686). However, in a more recent qualitative study exploring the factors that affect consumers' intention to use a mobile delivery app in South Africa, facilitating conditions were reported to prominently affect behavioural intention (Musakwa, 2021: iii).

According to Ho and Amin (2019: 34), facilitating conditions, in the context of mobile apps, refer to aspects of technology such as Internet access, mobile device functionality and other technology features that are no longer essential in the era of smartphone technology. Chotigo and Kadono (2021: 8) agree, arguing that facilitating conditions are irrelevant in exploring the adoption of food delivery apps, as these types of apps are common and omnipresent in Thailand. Nevertheless, Chopdar et al. (2018: 113) are of the opinion that users of mobile shopping apps require various skills and resources at their disposal, such as a stable Internet connection, the capability of downloading and installing different apps, and the skills to use these apps. Appropriate facilitating conditions are essential for the acceptance of technology and may vary meaningfully across technology providers in the consumer market (Palau-Saumell et al., 2019: 6; Vinnik, 2017: 34). As a result, a complementary set of facilitating conditions will improve the possibility of consumers accepting and using mobile shopping apps, and therefore warrants further investigation in the context of same-day delivery apps in South Africa.

Based on the discoveries discussed above, it can be argued that if users of mobile apps have the necessary facilities, resources and support available, they will have intent to use the specific technology (Hew et al., 2015: 1284; Zhou, 2012: 140). Users therefore need to have access to the Internet, a stable Internet connection or access to mobile data, knowledge of mobile apps, a smartphone with the capability of downloading mobile apps, location-finding technology on their mobile phones and specific information regarding same-day delivery apps, to use these apps successfully.

The research study investigated the same significance of facilitating conditions in the context of same-day delivery apps in South Africa and proposes the following:

Hypothesis 3: *There is a significant relationship between facilitating conditions and consumers' behavioural intention to continue using same-day delivery apps.*

The fourth construct of the UTAUT2 Model that was included in the conceptual model will be discussed in the next section.

4.2.5 SOCIAL INFLUENCE

Social influences occur when individuals are predisposed by the thoughts, opinions, behaviours, attitudes and feelings that result from interactions with others, which are then considered to be socially acceptable behaviours, be they intentional or unintentional (Rashotte, n.d.). Individuals generally develop intention towards technology when encouraged and motivated by the people close to them and whose opinions they value.

Social influence, as a direct determinant of behavioural intention, was operationalised in the development of the UTAUT Model by combining 'subjective norms' from the TRA, TAM2, TPB/D-TPB and C-TAM-TPB, 'social factors' from the MPCU and 'image' from the IDT (Venkatesh et al., 2003: 451). These constructs from various existing theories were merged due to their conceptual resemblance (Venkatesh et al., 2003: 451). Venkatesh et al. (2012: 159) explain that social influence refers to the extent to which an individual perceives that important others, such as peers, family, friends, or colleagues, believe they should use a particular technology. A consumer's decisions are highly influenced and shaped by the suggestions, comments, reviews and posts of significant others and other users (Malik, Suresh & Sharma, 2017: 109). Hew et al. (2015: 1273) point out that social influences can be twofold as consumers are influenced either by mass media, such as newspapers, television, the Internet, social media and radio, or by their interpersonal influencers, such as their relatives, peers, friends and colleagues (Chopdar et al., 2018: 113; Hew et al., 2015: 1273).

Prior research studies have demonstrated the significance of social influence on behavioural intention and empirically established its substantial impact on predicting consumers' intention to use m-commerce apps (Lian & Yen 2014: 133; Verkijika, 2018: 1672) and shopping apps (Chopdar & Sivakumar, 2019: 42; Miladinovic and Xiang, 2016: 22; Tak & Panwar, 2017: 12). The construct of social influence, and its impact on behavioural intention, has also been studied in the

context of on-demand service delivery apps (Elango et al., 2019: 1) and food delivery services and/or apps (Karulkar et al., 2019: 158; Lee et al., 2019: 9; Muangmee et al., 2021: 1297; Yapp et al., 2018: 105; Zhao & Bacao, 2020: 10), albeit limited. One such study, conducted by Elango et al. (2019: 1), investigated the factors impacting Bangkok consumers' intention to use on-demand delivery apps, and found social influence to have the most noteworthy impact on individuals' behavioural intention. Several scholars concur with these findings, as in their respective studies, social influence was found to positively affect the intention to use food delivery services and/or apps (Karulkar et al., 2019: 158; Lee et al., 2019: 9; Yapp et al., 2018: 105). Zhao and Bacao (2020: 8) explored the use of food delivery apps during the COVID-19 pandemic and state that social influences positively affected users' continuance intention behaviour. These findings were verified by Muangmee et al. (2021: 1307) who also investigated the factors determining the behavioural intention of using food delivery apps during the COVID-19 pandemic and came to the same conclusion that social influence has a noteworthy impact on behavioural intention.

Contradictory to the significant impact of social influence reported in the literature, an insignificant relationship was also reported. In understanding the determinants of continuance intention to use a specific on-demand mobile app in Indonesia (GO-JEK), Erwanti et al. (2018: 14) could not find social influences to significantly impact behavioural intention. The findings of Flores and Castaño (2020: 25) and Rasli et al. (2020: 679) coincide as they could also not find a substantial relationship between social influences and the behavioural intention to use food delivery apps in the Philippines and Malaysia, respectively. In a South African study, Musakwa (2021: iii) found no effect of social influence on the usage intention of mobile delivery service apps.

Although some researchers report social influence to be insignificant, the slower-than-average penetration of the Internet and related technologies in emerging economies such as South Africa means that societies will gradually increase their degree of trust in new mobile apps as others around them do. This is related to social influences, insofar as individuals of societies in emerging countries exert significant influence on one another in terms of accepting and adopting or using new technologies (Van Niekerk, 2020: 140). Van Niekerk (2020: 170) cautions that organisations operating within the m-commerce domain should be aware of the power of social influence. As users become more familiar with mobile shopping apps, especially same-day delivery apps, they will begin to talk about them, informing friends and family about them and convincing them to try the technology as well. Researchers argue that the more experienced a consumer is with using an m-commerce app, the less likely they are to believe that their friends, family and peers will

influence their decision to shop using their mobile phones (Miladinovic & Xiang, 2016: 22; Van Niekerk, 2020: 145; Verkijika, 2018: 1672).

Consumers' behavioural intention to use new technology are predicted to be influenced by social influence, such as same-day delivery apps, and therefore the inclusion of the construct was considered essential. Chong (2013: 528) and Zhou (2012: 137) argue that when those people that are closest to an individual start using a specific technological innovation, the probability is high that the individual will be influenced or convinced to adopt the technology as well. As a result, the research study assumed the same significant relationship by hypothesising the following:

Hypothesis 4: *There is a significant relationship between social influence and consumers' behavioural intention to continue using same-day delivery apps.*

The fifth construct from the UTAUT2 Model, namely hedonic motivations, will be examined in the following section as a factor that influences consumers' intention to continue using same-day delivery apps.

4.2.6 HEDONIC MOTIVATIONS

Venkatesh et al. (2012: 161) describe hedonic motivation, introduced in the UTAUT2 Model, as "… the fun or pleasure derived from using a technology". Hedonic shopping motivations, derived from perceived enjoyment, are an individual's motive to shop based on emotional responses, sensory pleasures, dreams and aesthetic considerations (Kusuma et al., 2013: 242). From a mobile app point of view, hedonic motivations signify customers' need for pleasure, enjoyment, or entertainment that can be obtained from their engagement with a particular mobile app (Mavuya, 2016: 17).

Hedonic motivation (conceptualised as perceived enjoyment) has been proven to play a vital role in determining technology acceptance behaviours in information systems research (Alalwan et al., 2017: 106; Brown & Venkatesh, 2005: 406; Uitz & Koitz, 2013: 130; Venkatesh et al., 2012: 161). It is argued that if technology is pleasurable to use, individuals can gain gratification from it, which ultimately influences their intention to pursue the technology (Lee, 2009: 852).

Hedonic motivation and its influence on behavioural intention have been tested extensively in the domain of m-commerce, mobile shopping and mobile apps (e.g. Chopdar et al., 2018: 122; Escobar-Rodríguez & Carvajal-Trujillo, 2014: 84; Hew et al., 2015: 1269; Miladinovic & Xiang,

2016: 50; Verkijika, 2018: 1668). Research reporting a significant relationship between hedonic motivation and behavioural intention to use on-demand mobile service apps, or food delivery apps, was limited. Yeo, Goh and Rezaei (2017: 157), for instance, examined the structural relationship between hedonic motivation and behavioural intention towards online food delivery services, among other things, and report a positive relationship between hedonic motivation and behavioural intention. Corroborated by Flores and Castaño (2020: 37), they also found hedonic motivation to be a noteworthy predictor of consumers' purchase behaviour towards food delivery apps. Rasli et al. (2020: 685) concur, as they too discovered a positive relationship between hedonic motivation and behavioural intention to continuously use online food delivery apps. In a South African study, Musakwa (2021: 60) reports the same significant relationship with behavioural intention to use a specific same-day delivery app (Checkers Sixty60).

Opposing findings pertinent to delivery service apps were also reported. Karulkar et al. (2019: 157) and Lee et al. (2019: 9) found hedonic motivation to be insignificant in influencing individuals' intention to use online food delivery services or food delivery apps. Hedonic motivation was also found to be irrelevant in the adoption of on-demand mobile services (Erwanti et al., 2018: 9). Yapp et al. (2018: 105) found that female consumers were significantly impacted by hedonic motivations to use on-demand services, whereas male consumers were unaffected. In their conceptual research paper, Pauzi et al. (2017: 4) state that consumers with strong hedonistic motivation will enjoy the process of finding information about the products online and tend to spend more time searching, comparing and selecting the online store and product. Since emotions, derived from fun, pleasure and enjoyment, are involved in the acceptance of technology systems, hedonic motivation is a strong predictor of adoption (Tak & Panwar, 2017: 252). Thus, it is argued that hedonistically motivated consumers will find more information about online shopping as they feel overwhelmed and content with what they do (Pauzi et al., 2017: 4).

It is argued that the number of individuals that are turning to food delivery in recent years has increased due to the current pace of life and the opportunity to discover more restaurants or retailers that offer delivery services (Rasli et al., 2020: 683). It is furthermore indicated that the intention to use mobile apps will increase the more users find it to be enjoyable (Miladinovic & Xiang, 2016: 50; Rasli et al., 2020: 683). Using m-commerce apps could give the impression of living a modern lifestyle, evoking feelings of happiness (Van Niekerk, 2020: 143). The pleasure resulting from the use of new technology, such as same-day delivery apps, is argued to be a contributing factor in the intention to use the technology, and hence its inclusion in the research study. It can be inferred that if users of mobile shopping apps find the various functions and

features to be fun, enjoyable, entertaining and pleasurable, they will have a favourable intention to use the app.

The aforementioned research studies, albeit contradictory in their findings, reinforce the argument that hedonic motivation has a significant influence on the behavioural intention of consumers to use mobile apps. Based on the literature discussion, it was assumed that hedonic motivation will have the same significant effect on consumers and the following is therefore hypothesised:

Hypothesis 5: *There is a significant relationship between hedonic motivations and consumers' behavioural intention to continue using same-day delivery apps.*

As previously discussed, food delivery services have changed consumers' behaviour considerably, and Chai and Yat (2019: 63) are of the opinion that online food delivery services have become the norm and part of people's daily routine. It is therefore inferred that using same-day delivery apps would become a habitual occurrence, and the inclusion of habit in the research study was deemed significant. The sixth UTAUT2 construct, namely habit, will be explored in the next section.

4.2.7 HABIT

'Habit' has been operationalised in many different ways by several authors. Kim and Malhotra (2005: 12) describe habit as similar to prior behaviour, while Limayem et al. (2007: 705) describe habit as the extent to which individuals believe that their behaviours are automatic. Habit has also been contextualised as involuntary and unconscious behaviour that is goal-directed (Limayem et al., 2007: 710-714) and is recognised with automaticity (Kim et al., 2005: 419). Venkatesh et al. (2012: 161) describe habit, in the context of the UTAUT2 Model, as the degree to which individuals tend to perform a specific behaviour or use specific technologies automatically, because of learning and previous experiences. Habit is therefore considered twofold as being a result of prior experiences and learning and also the degree to which an individual believes a particular behaviour is automatic (Van Niekerk, 2020: 145). Increased experience in usage will lead to habitual technology use (Kit, Ni, Badri & Yee, 2014: 12). Van Niekerk (2020: 145) agrees, arguing that the continued use of mobile apps leads to the formation of new habits. Thus, habit is defined for the purpose of the research study as the degree to which the use of technology, due to learning, would become automatic, habituated and a natural occurrence to the user.

Habit and its influence on behavioural intention have been extensively investigated in the m-commerce domain. Prior research has empirically recognised habit as a key factor influencing consumers' behavioural intention to adopt mobile apps (e.g. Gupta et al., 2018: 145; Mutlu & Der, 2017: 179; Tak & Panwar, 2017: 248) and mobile shopping apps (e.g. Chopdar & Sivakumar, 2020: 42; Lee et al., 2019: 1; Miladinovic & Xiang, 2016: 45; Phang, Zaiton & Cheuk, 2018: 18; Van Niekerk, 2020: 269). Research relating to the intention of individuals to adopt same-day delivery apps is, however, scant. Research associated with on-demand service apps, food delivery services and/or apps is therefore reported in support of the inclusion of the habit construct in the conceptual model.

In a study extending the UTAUT2 Model to identify the determinants of continuous use intention of food delivery apps, Lee et al. (2019: 9) found habit to have the strongest influence on continuous use intention. These findings are in line with other scholarly research, such as Erwanti et al. (2018: 9), Flores and Castaño (2020: 38) and Rasli et al. (2020: 685), who also report significant influences of habit on the intention to adopt on-demand mobile service and/or food delivery apps in Indonesia, the Philippines and Malaysia. In a South African study, however, habit was found to be insignificant in the adoption of a specific same-day delivery app (Checkers Sixty60) (Musakwa, 2021: 58). The insignificant relationship between habit and behavioural intention could be because the intention to use specific technological systems will become less significant as the habit becomes stronger (Escobar-Rodríguez & Carvajal-Trujillo, 2014: 83). Researchers argue that as individuals become accustomed to and content about using mobile apps, such as same-day delivery apps, the chances of the action or activity being repeated and becoming an occurrence of habit increase (Alalwan, 2020: 33; Erwanti et al., 2018: 9; Flores & Castaño, 2020: 38; Rasli et al., 2020: 685). Such behaviour gradually evolves into habit, where users find that they must use mobile apps in their daily/weekly routines.

Since consumers utilise a variety of technologies daily, they become unconsciously dependent on technology, including mobile apps, which is considered a significant driver of intention to use technology (Hew et al., 2015: 1285). Phang et al. (2018: 23) concur and contend that users who are familiar with a mobile app would naturally use mobile shopping apps and eventually their use would become habitual. According to Wang, Malthouse and Krishnamurthi (2015: 2), mobile devices are an effective platform for customers to develop habitual interactions with a retailer because mobile devices provide convenience and are an integral part of consumers' daily routines. Consumers are likely to develop the same habit toward same-day delivery apps because they are simple to use and provide the convenience of having products delivered to their preferred location on the same day.

The above literature discussion on the mobile app and delivery service app industries suggests that the use of same-day delivery apps has likely become a behaviour of habit, and the following is thus hypothesised:

Hypothesis 6: *There is a significant relationship between habit and consumers' behavioural intention to continue using same-day delivery apps.*

Price value is the last construct used from the UTAUT2 Model to predict consumers' behavioural intention to utilise same-day delivery apps. The discussion of price value in the context of the research study follows.

4.2.8 PRICE VALUE

During the development of the UTAUT2 Model, Venkatesh et al. (2012: 158) included a price or cost component in establishing behavioural intention from a consumer's point of view. Price value was included in the UTAUT2 Model because price is a significant factor in a consumer technology use context since, unlike workplace technologies, consumers must bear the costs associated with using technology (Venkatesh et al., 2012: 158). The cost and pricing structure pertaining to the innovation may have a substantial impact on consumers' behavioural intention towards the technology. Venkatesh et al. (2012: 161) describe price value as "… consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost of using it". Consumers therefore look for higher perceived benefits in comparison to the monetary sacrifice (Gupta et al., 2018: 58). Price value will be positive if the benefit of using a technological system or device is perceived to be greater than the monetary cost and as such, price value has a positive impact on intention (Tamilmani, Rana, Dwivedi, Sahu & Roderick, 2018: 2; Venkatesh et al., 2012: 161).

In the context of technology acceptance and use, financial costs play a fundamental part in moulding consumers' readiness to accept technology, such as same-day delivery apps. To use same-day delivery apps, consumers must first download and install the app using an Internet data bundle, and will then need to buy data bundles for their mobile device to continually use the app. Furthermore, most same-day delivery apps charge a small service fee and/or a delivery fee for each order placed through the app. Given that mobile data costs are high in South Africa (Thusi, 2018: 57), and due to the service or delivery costs involved in using same-day delivery apps, customers are expected to engage in conscious decision-making to weigh the benefits of using same-day delivery apps against the costs. As a result, it was projected that price value will play a

decisive role in consumers' continuance acceptance of same-day delivery apps in a South African context.

Correspondingly, prior research validated the significance of price value in determining consumers' behavioural intention. Users of same-day delivery apps might feel that the cost incurred on the app and the benefits derived from using such apps are comparable. Price value was considered an important determinant of continuous intention to use on-demand mobile service apps (Erwanti et al., 2018: 9; Flores & Castaño, 2020: 25). These findings are supported by Saad (2021: 535) and Rasli et al. (2020: 679). Saad's study explored the factors that affect the choices of consumers while ordering food online in Bangladesh and found price value to be significant. Rasli et al. explored the determinants of continuous use intention of online food delivery apps by extending the UTAUT2 Model with information quality. In their study, Rasli et al. (2020: 687) discovered that price value and information quality have the most influence on behavioural intention. In similar studies, price value was found to have a noteworthy impact on the intention to adopt mobile shopping apps (Chopdar et al., 2018: 117; Tak & Panwar, 2017: 12), mobile shopping fashion apps (Khurana & Jain, 2019: 757), mobile apps in general (Fadzil, 2018: 1), phablets (Huang & Kao, 2015: 19) and smartphones (Ameen & Willis, 2018: 16), among others.

Contrasting results have also been reported. Lee et al. (2019: 9) and Yapp et al. (2018: 117-119), for instance, both found that price value does not affect users' continuous intention to use food delivery apps or on-demand service apps. In a qualitative study, Musakwa (2021: iii) explored the factors that influence South African consumers' intention to use a specific same-day delivery app (Checkers Sixty60) by analysing the reviews on the Google Play Store. Musakwa (2021: 55) reports that, although price value raised many concerns from the reviewers, there was little effect on users' intention to use the specific mobile app. In another South African study, price value also did not have a positive influence on behavioural intention to use m-commerce apps to purchase athleisure apparel (Van Niekerk, 2020: 10). South Africans tend to be more price conscious in general, considering the fact that spending is constantly under pressure. Furthermore, they have reduced their spending and begun delaying purchases as they compare options to find the best price (Van Niekerk, 2020: 273). This theory is in line with Hew et al. (2015: 1284) as well as Miladinovic and Xiang (2016: 51).

The aforementioned arguments indicate that price value is a strong predictor of behavioural intention and therefore the following hypothesis is made:

Hypothesis 7: *There is a significant relationship between price value and consumers' behavioural intention to continue using same-day delivery apps.*

Sections 4.2.2 to 4.2.8 provided a detailed account of each of the UTAUT2's constructs as well as the significance of each construct to the field of mobile app adoption behaviours, and more specifically on-demand mobile service apps (or where applicable, same-day delivery apps). The same approach is used in sections 4.2.9 to 4.2.12 in the discussion of the four additional exogenous constructs. The research study further built on the UTAUT2 Model by incorporating four exogenous mechanisms to determine their significance on consumers' behavioural intention to continue using same-day delivery apps in South Africa. The additional constructs are lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. The first exogenous construct considered for the research study was whether same-day delivery apps are perceived to be compatible with consumers' lifestyles. The exogenous construct will be discussed in the following section.

4.2.9 LIFESTYLE COMPATIBILITY

Seminal author Albert Bandura (1986) developed Social Cognitive Theory (SCT) and defines human behaviour as a triadic, dynamic and reciprocal interaction of personal factors, behaviour and the environment (in Al-Mamary et al., 2016: 145). Many researchers have since explored the impact of personal factors on the behaviour of individuals. Rogers (1995, in Boateng et al., 2016: 471), among others, notes that certain individuals accept a technological innovation if it is compatible with their lifestyle. From a sociological approach, research has recognised lifestyle as a key determinant of an individual's intention to adopt products, services and brands (Belanche et al., 2020: 1). In today's fast-paced world, and with the heightened use of technologies, individuals are increasingly coerced to make purchases through mobile apps (Belanche et al., 2020: 1). Accordingly, lifestyle compatibility influences individuals' behaviour and consumption choices, thus offering marketing researchers added insight into predicting consumers' behaviours, specifically their intention to use new technology (Shaw & Sergueeva, 2019: 48).

Lifestyle is defined as the activities, interests, opinions, behaviours and behavioural orientations of an individual, group or culture (Belanche et al., 2020: 7; Mirriam-Webster, 2021), and is considered a way of living (Housman & Odum, 2020: 3). Conversely, lifestyle compatibility is the natural alignment of lifestyle choices and values (Yang, Mamun, Mohiuddin, Nawi & Zainol, 2021: 5), and refers to the degree to which individuals perceive that a particular technology is well suited to the way they think, act and lead their lives (Boateng et al., 2016: 471). From an online shopping

perspective, lifestyle compatibility signifies the beliefs and values that an individual holds with regard to shopping online, and how well the activity of shopping online fits into the consumer's routine and life (Cuna, 2020: 9). For the purpose of the research study, same-day delivery apps can be argued to be compatible with a consumer's lifestyle if the user perceives the app to fit in with the way they live, work and conduct themselves socially.

The significance of lifestyle compatibility has grown in importance because of the countless types of technological innovations available to consumers. It is therefore argued, and widely researched, that the compatibility of technology with an individual's lifestyle may influence their intention to use the specific technological innovation. Belanche et al. (2020: 1) assert that individuals search for alternatives to make everyday tasks easier and more suited to their lifestyles.

Previous research observed that lifestyle compatibility is an important and contributing factor in the adoption and use of new technology (Belanche et al., 2020: 14; Leung & Chen, 2017: 1639). This implies that individuals tend to adopt those technologies that are compatible with their values, norms, past experiences and self-perception. Research supports this statement as numerous researchers have proven that perceived lifestyle compatibility has a significant influence on consumers' attitudes and behavioural intention (Boateng et al., 2016: 468; Yang et al., 2021: 1). While many scholars explored lifestyle compatibility in the banking industry (e.g. Boateng et al., 2016: 468; Chawla & Joshi, 2017: 410; Shankar & Kumari, 2016: 14; Yang et al., 2021: 1), limited research could be found on same-day delivery apps, on-demand service apps or food delivery apps. Arora and Malik (2020: 98) explored the significance of lifestyle compatibility regarding mobile apps among Indian consumers and found a significant relationship between lifestyle compatibility and usage intention. One study examined the phenomenon of food delivery services from the mobile app user's perspective and how consumers' lifestyles are changing because of the convenience of these apps (Belanche et al., 2020: 1). Belanche et al. (2020: 7) are of the opinion that consumers are accustomed to using apps, to the point where the apps are fully integrated into their daily lives, and consequently proposed that, in the growing food delivery app sector, consumers may have already developed lifestyle compatibility with continuous app use, which could affect their intention to use the apps. Belanche et al.'s study (2020: 13) further revealed that mobile app lifestyle compatibility had a positive and significant influence on the intention to use food delivery services.

In a South African study by Cuna (2020: 60) determining which website design features have an influence on the purchase intentions of consumers, lifestyle compatibility was found to be insignificant. Cuna's findings indicate that the sample did not place much value on lifestyle

compatibility when deciding whether to make a purchase online. According to Belanche et al. (2020: 14), customers' intentions to use food delivery apps are influenced by their lifestyles, implying that this factor should not be overlooked when investigating consumers' adoption of everyday technologies. The significance of lifestyle compatibility has furthermore been proven by several scholars, and because its impact on consumers' adoption of same-day delivery apps is limited, it was deemed fit to include lifestyle compatibility in the research study. It is inferred that the more a consumer feels that shopping on mobile apps and conveniently having products delivered to their door on the same day suit their lifestyle, the more intention they will have to adopt the mobile app and make a purchase (Cuna, 2020: 23).

The emergence of food delivery services could be attributed to the changing nature of the urban consumer (Chai & Yat, 2019: 63). Home delivery services, such as same-day or on-demand delivery apps, are convenient for online shoppers (Chen, Hsu, Hsu & Lee, 2014: 69), and consumers seek quick and convenient meals during or after a busy workday (Chai & Yat, 2019: 63). In addition, due to the advancements in mobile apps, home delivery services have become even more valuable because of the current pace of life and the opportunity to discover more restaurants and retailers that offer home delivery services (Belanche et al., 2020: 1; Chai & Yat, 2019: 63).

The above discussion indicates that lifestyle compatibility is considered a significant predictor of behavioural intention and affirms the inclusion of the construct in the research study. The same significant relationship as discussed above was accepted in this study and the following hypothesis is formulated:

Hypothesis 8: *There is a significant relationship between lifestyle compatibility and consumers' behavioural intention to continue using same-day delivery apps.*

Although the literature proves various determinants that positively impact individuals' acceptance of mobile apps, individuals have some doubts when purchasing online or on mobile apps (Pauzi et al., 2017: 1). Major deterrents that impede consumers from shopping online or via mobile apps are the perceived risks and lack of trust (Pauzi et al., 2017: 1). It was believed that incorporating perceived risk in the context of the research study would help increase the applicability and predictive power of the conceptual model. The aim of the research study was therefore to investigate whether perceived risks influence South African consumers' behavioural intention to continue using same-day delivery apps. The risk consumers perceive in using technology, and specifically mobile shopping apps, is discussed in the subsequent section.

4.2.10 PERCEIVED RISK

With the rapid evolution of smartphones and the widespread use of smart technology worldwide, mobile devices offer cutting-edge and functional operating system enhancements that give users a more convenient and effective way of life (Marriott & Williams, 2018: 1). In addition, m-commerce, which includes a variety of online services accessible through mobile devices and across mobile websites and apps, has emerged as one of the most conspicuous social changes within the last decade. M-commerce provides consumers and retailers with more opportunities, faster access and greater accessibility (Marriott & Williams, 2018: 1).

Despite the exponential growth of the mobile app market (as discussed in Chapter 2), this growth has been accompanied by a rise in mobile users' apprehension about using mobile apps (Belanche et al., 2020: 6). Many researchers have acknowledged that one of the main factors hindering the adoption of online or mobile app shopping is users' concern about privacy and security (e.g. Chopdar et al., 2018: 3; Hubert et al., 2017: 181; Kaushik et al., 2020: 12). According to Alaimo, Fiore and Galati (2020: 3), consumers' perceptions of the risks associated with the acceptability and usage of modern technologies, as well as their own personal qualities are significant predictors of their intentions to use these tools to make purchases. Investigating how perceived risk affects consumers' behavioural intention to continue using same-day delivery apps in a South African context, along with other predictors of the UTAUT2 Model, was expected to yield practical insights for both academics and industry; hence its inclusion.

In the context of m-commerce, perceived risk is conceptualised as "… a potential loss as perceived by a customer while shopping online using mobile retail apps when compared to purchasing products offline" (Kaushik et al., 2020: 12). In the context of online or mobile shopping, perceived risk refers to consumers' perceptions regarding the potential risks they may be exposed to as a result of transacting online (Van Niekerk, 2020: 148). Perceived risk therefore signifies an individual's degree of uncertainty about the outcomes of their decision to purchase online or via mobile apps (Pauzi et al., 2017: 5).

Purchasing online or via mobile apps poses different risks to individuals which may impede their intention to purchase online or via mobile apps, for example: (1) the potential loss of control of personal information, such as payment information, address and telephone number, (2) concerns that personal information could be misused, (3) concerns that mobile transactions will lead to transaction fraud, (4) the inability to examine products before buying them – such as concerns of the quality or freshness of the products or not being able to judge the size, texture or colour of the

products, (5) the risk of having a stranger deliver the order to their home and the physical contact with the driver, (6) the waiting period for products to arrive and (7) the time that online retailers take to handle unsatisfactory product returns or complaints (Dawi, 2019: 117; Pauzi et al., 2017: 5, Van Niekerk, 2020: 32). Researchers have found that perceived risk is more prevalent when shopping online because of the physical distance between sellers and buyers (Gupta et al., 2018: 54). Regardless of the many advantages and opportunities offered by same-day delivery apps, they may also involve a high risk of privacy violations as users' personal information, such as their contact details, location information and payment information, must be disclosed and can be compromised (Yun et al., 2013: 217). Perceived risk is considered to be a decisive barrier for consumers purchasing a product via a mobile shopping channel, such as same-day delivery apps (Van Niekerk, 2020: 148).

Several scholars have explored perceived risk as a second-order construct, arguing that perceived risk is influenced by various sub-dimensions, such as privacy, security, financial, product performance, psychological, time/convenience, social, physical and device risks (e.g. Chen, 2015: 61; Chin, Harris & Brookshire, 2018: 54; Chopdar et al., 2018: 18; Fortes & Rita, 2016: 168; Hussein & Saad, 2016: 40; Marriott & Williams, 2018: 8; Thusi & Maduku, 2019: 345; Van Niekerk, 2020: 148). The effect of perceived risk as a singular, or first-level construct, on adoption behaviour has been both supported (e.g. Ali & Maideen, 2019: 370; Chang, Liu & Shen, 2017: 207; Gupta et al., 2018: 50; Kaushik et al., 2020: 1; Marriott & McLean, 2019: 1) and rejected in the literature (e.g. Monilakshmane & Rajeswari, 2018: 153). Scholars have furthermore reported a negative association between perceived risk and intention towards online purchases in different sectors, such as banking (e.g. Hussein & Saad, 2016: 40; Kaushik & Rahman, 2015: 96; Monilakshmane & Rajeswari, 2018: 153), tourism (e.g. Amaro & Duarte, 2015: 98; Gupta et al., 2018: 50), retailing (e.g. Alaimo et al., 2020: 1; Arora & Malik, 2020: 1; Kaushik et al., 2020: 1; Marriot & McLean, 2019: 1) and hospitality industries (e.g. Kaushik, Agrawal & Rahman, 2015: 278), among others. Verification of perceived risk as a singular construct is of particular theoretical importance and could provide valuable academic and practical understanding of the intention behaviours among customers, particularly in a developing country such as South Africa.

Perceived risk has more recently been studied within the m-commerce domain, with the majority of the research supporting the inclusion of perceived risk within the behavioural intention research model (Marriott & McLean, 2019: 4). For example, Kaushik et al. (2020: 1) as well as Marriott and McLean (2019: 4) report that perceived risk significantly influences an individual's behavioural intention to adopt mobile retail apps or shopping apps. Arora and Malik (2020: 106) concur as their study revealed that security, a sub-dimension of risk as reported by some researchers, has the

most significant effect on usage behaviour regarding mobile apps in India. In their study exploring the factors that influence the adoption of a crowdsourcing mobile app among Generation Y and Z consumers in the Maldives, the relationship with intention was found to be noteworthy (Ali & Maideen, 2019: 375). In a South African study, Van Niekerk (2020: 10) explored the effect of two sub-categories of risks (i.e. financial risks and performance risks) on the adoption of m-commerce apps to purchase athleisure apparel. The results did not reveal perceived risk as having an influence on behavioural intention. Van Niekerk (2020: 274) argues that the insignificance of perceived risk in that study could be an indication that younger South Africans are less risk-averse to potential risks associated with shopping for athleisure apparel online or through a mobile device.

Research related to same-day, or on-demand delivery apps, is scant. Related research that has been conducted explored the factors that influence consumers' intention to purchase groceries online (Pauzi et al., 2017: 1), and investigated which characteristics affect the decision of online food shopping during the COVID-19 pandemic in Italy (Alaimo et al., 2020: 1). Customers' repeat purchase intention of mobile food service apps was explored by Ahn (2019: vi), who considered perceived risk as a potential moderating variable. Chai and Yat (2019: 62) aimed to establish an integrated model that investigates the relationship between privacy and security, among other things, and the behavioural intention towards online food delivery services in Malaysia. In the context of Chai and Yat's study (2019: 66), privacy refers to the probability to access, copy, use and destroy personal information, and security is the threat which creates potential occurrences related to the security of payment and storing of information through online transactions. Similarly, Belanche et al. (2020: 1) examined the phenomenon of food delivery services from the mobile app user's perspective but focused on the influence of perceived security. In the context of Belanche et al.'s study (2020: 6), perceived security refers to "… the perception of the app provider's appropriate actions to safeguard shared information from security breaches during and after transmission through the mobile phone". The sub-dimensions explored by Chai and Yat and Belanche et al. are closely related to, and encompass, the perceived risk individuals may experience when using same-day delivery apps and theirs was the closest research pertaining to the research study that could be found. Exploring the effects of perceived risk in the context of same-day delivery apps would contribute meaningfully to the current knowledge base on m-commerce, mobile apps and behavioural intention research.

An inverse relationship between consumers' perceived risk and behavioural intention has been widely reported in existing literature, which suggests that individuals with high perceived risk are more likely to avoid mobile retail apps and might choose offline retailing as their preferred medium to shop (Kaushik et al., 2015: 22; Vasileiadis, 2014: 187; Verkijika, 2018: 1673). The empirical

results reported in the literature support the notion that perceived risk is considered a strong predictor of behavioural intention and affirm its inclusion in the research study.

From the literature discussion above, it is apparent that perceived risk has been a common extension of the UTAUT2 Model and, unlike the driving constructs included in the UTAUT2 Model, perceived risk represents a detractor in the adoption process (Slade et al., 2015: 864). Since research has attested that perceived risk has a negative effect on intentions, the same adverse relationship was assumed in this study and the following hypothesis is formulated:

Hypothesis 9: *There is a significant and negative relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps.*

The literature has shown that the lower the perceived risk associated with using technology, the more trust individuals will have in the specific technology. Consequently, lower perceived risks and increased trust lead to satisfactory transactions, reduce uncertainty and enhance m-commerce adoption, if individuals have confidence in its use, which is denoted by the concept of self-efficacy (Singh et al., 2018: 115). Perceived self-efficacy was therefore investigated to be included in the research study and is acknowledged by prior research as a strong predictor of behavioural intention. The significance of perceived self-efficacy, in the context of the research study, was investigated and its relevance is discussed in the next section.

4.2.11 PERCEIVED SELF-EFFICACY

Self-efficacy, in the context of information systems technology, was first introduced by Compeau and Higgins in 1995, who applied and extended Bandura's SCT to the context of computer utilisation. Compeau and Higgins (1995: 189) found that performance expectations, outcomes expectations (personal), self-efficacy, affect and anxiety influence computer utilisation. Venkatesh et al. (2003: 432) examined the predictive validity of Compeau and Higgins' model in the context of behavioural intention and usage, to allow a fair comparison of the model in the development of the UTAUT Model. Although self-efficacy appeared to be a significant direct determinant in the SCT, Venkatesh et al. (2003: 455, 461) did not include it in the UTAUT Model, arguing that self-efficacy is conceptually and empirically comparable to the 'effort expectancy' construct, and that self-efficacy does not have a significant direct effect on intention due to the effect being captured by 'effort expectancy'.

Moghavvemi et al. (2013: 247) are, however, of the opinion that inexperienced users view new technology as complex, and the confidence a person has in their ability to handle new technology has a substantial influence on its acceptance. A higher level of perceived self-efficacy will therefore lead to higher intentions to adopt and use the technology. Moghavvemi et al. (2013: 249) propose the inclusion of perceived self-efficacy in the UTAUT Model to address the limitation posed by the model – to measure individual characteristics towards behavioural intention to adopt the technology. Furthermore, because same-day delivery apps for groceries were still relatively new in South Africa during the time of the current study, both customers and retailers may have been influenced by users' lack of familiarity with and confidence in their ability to use such apps. Moreover, there is a lack of research on the adoption of same-day delivery apps, particularly in South Africa. It was anticipated that the inclusion of self-efficacy would provide valuable insight into m-commerce and mobile app adoption behaviour research in a developing country. The preceding arguments validate the inclusion of the perceived self-efficacy construct in the research study.

From an organisational setting, self-efficacy is contextualised as "… the judgement of one's ability to use a technology to accomplish a particular job" (Venkatesh et al., 2003: 432). Perceived self-efficacy represents a person's belief concerning their own capacity to carry out a specific task using technology or mobile devices, which is argued to significantly predict behavioural intention and adoption behaviours (Singh et al., 2018: 115). In the context of the research study, perceived self-efficacy signifies an individual's belief or perception in their own ability and self-confidence to complete a specific activity or task using a mobile device and app (Hu & Zhang, 2016: 645; Yul, 2014: 12).

Self-efficacy has been identified by several scholars as a determinant that significantly influences consumers' intention and adoption behaviour towards a specific technology (e.g. Lee & Hsieh, 2009: 1; Singh et al., 2018: 122; Wang & Wang, 2008: 405; Yul, 2014: 12-13). Reported empirical results confirm that self-efficacy implicitly affects consumers' intention to adopt fitness mobile apps (Wei et al., 2020: 1), telebanking (Alalwan, Dwivedi, Rana & Simintiras, 2016: 690), mobile banking services (Jeong & Yoon, 2013: 1; Singh et al., 2018: 121), payment systems (Makki, Ozturk & Singh, 2016: 454), m-commerce (Luarn & Lin, 2005: 873), mobile data services (Yang, 2010: 117), location-based services (McKenna et al., 2014: 12) and mobile computing (Wang & Wang, 2008: 405), to name but a few. Research related to same-day, or on-demand delivery apps, is limited. One such related study investigated the factors that impact the behavioural intention of consumers in Bangkok to use on-demand food delivery apps (Elango et al., 2019: 1). Elango et al. (2019: 13)

found personal self-efficacy to be the second most significant predictor of behavioural intention to use on-demand food delivery apps.

To establish self-efficacy in the context of mobile technology, mobile self-efficacy measures have been developed by various scholars who found self-efficacy to be valid in predicting users' intention to adopt new mobile innovations (Okumus & Bilgihan, 2014: 39; Wu et al., 2007: 65; Wang & Wang, 2008: 405). Gitau and Nzuki (2014: 91) note that besides being confident in exploring new technologies, high perceived self-efficacy allows an individual to perform the intended task on a mobile app more successfully. It is argued that the more self-efficacious users view themselves to be, the higher their intention to use technology will be (Okumus & Bilgihan, 2014: 39; Marriott et al., 2017: 576). Individuals with higher expertise will also have increased intentions to use a system compared to an individual with lower expertise (Jeong & Yoon, 2013: 35). Islam et al. (2011: 82) assert that individuals with high perceived self-efficacy are prone to adopt m-commerce more effectively as they expect the system to be user-friendly and easy to use and are as a result more likely to use m-commerce continuously.

Grounded in the theoretical validation discussed above, perceived self-efficacy is expected to significantly influence consumers' behavioural intention to use mobile apps (Okumus & Bilgihan, 2014: 39). It was considered vital to examine users' belief in having the required personal knowledge, skills, or abilities to use same-day delivery apps as well. Luarn and Lin (2005: 878), as well as Hu and Zhang (2016: 645) state that if users believe they have the ability to use certain mobile apps, their intention to use it will increase. The same view was adopted and the following is proposed:

Hypothesis 10: *There is a significant relationship between perceived self-efficacy and consumers' behavioural intention to continue using same-day delivery apps.*

Attitude towards using technology was considered a salient factor influencing consumers' behavioural intention towards using same-day delivery apps because the UTAUT Model was criticised for not considering individual characteristics (refer to Chapter 3, section 3.4.4). Empirical evidence supports the inclusion of attitude towards using technology as a strong predictor of behavioural intention and hence its inclusion in the conceptual model. The last exogenous mechanism incorporated in the conceptual model (see Figure 1.3) and its significance in the context of the research study are covered in the following section.

4.2.12 ATTITUDE TOWARDS USE

During the conceptualisation of the UTAUT Model, attitude towards using technology was defined as an individual's affective reaction to using a particular technology or system (Venkatesh et al., 2003: 455). Four constructs from existing models or theories align closely with the above definition of attitudes: 'attitude towards behaviour' taken from the TRA, TPB or D-TPB and C-TAM-TPB, 'intrinsic motivation' taken from the MM, 'affect towards use' taken from the MPCU and 'affect' taken from the SCT. These constructs were combined due to their operational similarities. Empirically, in the validation of the UTAUT Model, the attitudinal construct was only significant when specific cognitions (i.e. the performance expectancy and effort expectancy constructs) were omitted from the model. The observed relationships between attitude and intention were considered by Venkatesh et al. (2003: 455) as spurious. This means that attitude towards the use of technology does not provide enough unique information beyond that which is already provided jointly by the performance expectancy and effort expectancy constructs (Thomas et al., 2013: 73). Given that significant relationships between performance expectancy, effort expectancy and behavioural intention were expected, Venkatesh et al. (2003: 455) were of the opinion that attitude towards the use of technology would not have a direct or collaborative influence on behavioural intention and it was consequently omitted from the UTAUT Model.

In their assessment of the UTAUT Models, however, Moghavvemi et al. (2013: 247) maintain that Venkatesh et al. (2003) failed to measure individual characteristics towards behavioural intention to adopt technology (i.e. attitude and self-efficacy) (discussed in Chapter 3, section 3.4.4). Several renowned technology adoption theories, such as the TPB, TRA, TAM and C-TAM-TPB, found attitude to be a significant determinant of behavioural intention (Moghavvemi, 2015: 2). Earlier studies furthermore report attitude to be a salient direct determinant of behavioural intention (e.g. Van Dijk, Peters & Ebbers, 2008: 385; Oshlyansky, Cairns & Thimbleby, 2007: 1; Yuen et al., 2010: 52). Due to this limitation of the UTAUT2 Model, using solely the UTAUT2 Model as the foundational framework to establish consumers' adoption behaviours might not have been appropriate. The UTAUT2 Model might not have been able to capture the effect of attitude on consumers' intention, whereas this factor can be a significant determinant of consumer decision-making to adopt same-day delivery apps. Therefore, in an attempt to address the limitation of the UTAUT Models, the research study investigated the impact of consumers' attitudes towards using technology as a salient direct determinant in their intentions to continue using same-day delivery apps.

Attitudes, according to the seminal author Kotler (2000: 175), "… is a person's enduring, favourable or unfavourable evaluation, emotional feelings, and action tendencies towards the same object or idea". Attitude has long been a topic of interest in the field of marketing as it allows researchers, and marketers, to predict consumers' intentions and purchase behaviours (Khanal, 2018: 7). In the development of adoption and behavioural intention research, seminal authors such as Fishbein and Ajzen (1975), Davis (1989), Azjen (1991) and Taylor and Todd (1995) included 'attitude towards using' technology in the validation of the TRA, TPB, TAM and the C-TAM-TPB. All technology acceptance theories, according to Momani and Jamous (2017: 51), are intended to measure the degree of acceptance and individuals' level of satisfaction, but from different perspectives, depending on the constructs that represent their structure. The inclusion of attitude towards using technology in these renowned theories is briefly discussed to afford the conceptualisation of the construct and its proposed direct determinant on behavioural intention.

From the social psychology stream, the TRA, TPB, TAM and the C-TAM-TPB are only a few of the major modular approaches that have led the way in analyses and results (Tarhini et al., 2016: 832). The TRA was introduced in 1975 by social psychologists Fishbein and Ajzen in an effort to understand the relationship between individual beliefs, attitudes, intentions and behaviour (Tlou, 2009:16). The theory suggests that individuals' behavioural intention is affected by two major factors, namely individuals' attitudes towards performing the given behaviour and the subjective norms associated with the behaviour (Jen et al., 2009: 91; Tlou, 2009: 16).

The TRA assumes that an individual's attitude is determined by their beliefs about the outcome of performing a specific behaviour (Tlou, 2009: 16). Fishbein and Ajzen (1975: 5) define the attitude towards a behaviour as "… the individual's positive or negative feelings (evaluative effect) about performing the specific behaviour". Attitudes are a psychological construct that is shaped by thoughts (cognition), beliefs (value) and emotions (affection) towards a particular object (Al-Swidi, Huque, Hafeez & Shariff, 2014: 1564). Attitude is conceptualised as referring to the degree to which an individual favours the behaviour being performed and is established from behavioural beliefs and subjective outcome evaluations (Al-Debei et al., 2013: 45; Sanne & Wiese, 2018: 3; Utami, 2017: 479). In general, the theory postulates that if attitudes towards a behaviour are favourable, an individual will have stronger intentions, consequently resulting in a greater likelihood of engaging in the behaviour. On the contrary, if attitudes are unfavourable, individuals will have weaker intentions to engage in the behaviour and will be less likely to carry out that behaviour.

The TPB was developed in 1991 by seminal author Icek Ajzen. Ajzen (1991: 181) expanded the TRA (discussed above) in an attempt to address the original model's limitation in dealing with behaviours over which individuals have partial volitional control. The theory postulates three conceptually independent determinants of intention, namely attitude towards the behaviour, subjective norms and perceived behavioural control. Ajzen (1991:188) included the construct 'perceived behavioural control', which is a determinant of both intention to use and actual usage behaviour. The TPB holds that individuals' intention to perform a given behaviour will be stronger if the individual has a more favourable attitude and subjective norm with respect to the particular behaviour, and they have greater perceived behavioural control (Ajzen, 1991: 188; Janssen, 2009: 31).

Attitude towards the behaviour has been adapted from the TRA and is also conceptualised as "… the degree to which a person has a favourable or unfavourable evaluation or appraisal of the behaviour in question" (Ajzen, 1991: 188). Attitude towards a behaviour refers to "… the intention of the individual to use a technology based on the opinion of the social groups that are of importance to the individual and that approves or disapproves of the technology and/or behaviour" (Fishbein & Ajzen, 1975: 5; Miladinovic & Xiang, 2016: 13).

The TAM, first introduced in 1989 by seminal author Fred D. Davis, initially originated from the TRA (discussed above) that was used in social psychology to explain a wide range of individual behaviours (Gong & Yan, 2004: 445). The main goal of the TAM, however, is to provide a universal description of the factors that influence technology acceptance and to explain the behaviour of technology users across a broad range of technological systems and among various user populations (Davis et al., 1989: 895). TAM was specifically developed to be used within the information systems domain and predicts the behavioural intention and the use of information technology in a workplace environment (Algharibi & Arvanitis, n.d.: 527; Davis, 1989: 319; Wentzel et al., 2013b: 3).

According to the TAM, individuals' adoption of information technology is determined by their perception of the required effort (perceived ease of use) and the extrinsic motivator (perceived usefulness), which influences the individuals' acceptance of an information system (Davis et al., 1989: 985; Roback & Wakefield, 2013: 21). Like the TRA, the TAM assumes that technology usage is established by behavioural intentions; however, it differs in that behavioural intention is seen to be determined by an individual's attitude towards the system as well as the perceived usefulness of the technology (Davis et al., 1989: 985). Therefore, the TAM is expected to determine a person's

attitude towards the technology, which in turn determines their intention to use or adopt it (Davis et al., 1989: 985; Hamid et al., 2016: 645; Hussain, Mkpojiogu & Yusof, 2016: 2).

The C-TAM-TPB Model, developed and validated by seminal authors Taylor and Todd in 1995, combines two predictors of the TPB (subjective norm and perceived behavioural control) with the 'perceived usefulness', 'ease of use' and 'attitudes' constructs from TAM to provide an amalgamated model (Birch, 2009: 27). Taylor and Todd (1995: 145) criticised the TAM for failing to incorporate factors of society and behavioural control, which have been proven to affect actual or planned behaviour. They therefore combined the TAM and TPB to include the proven subjective norm and behavioural control constructs.

The C-TAM-TPB Model suggests that behaviour is influenced by an individual's intention, which in turn is influenced by their subjective norms and perceived behavioural control (adapted from the TPB), as well as individuals' attitude and perceived usefulness (adapted from the TAM) (Al-Mamary et al., 2016: 152). The C-TAM-TPB predicts that perceived behavioural control would have a direct and indirect influence on behavioural intentions (Al-Mamary et al., 2016: 152). Perceived usefulness and ease of use are determinants of attitude, whereas perceived ease of use directly affects perceived usefulness (Taylor & Todd, 1995). The empirical results reported by Taylor and Todd (1995) show that C-TAM-TPB has high fitness in explaining individuals' behaviours of using new technology (in Jen et al., 2009: 92).

It is evident from the literature discussion above that there are two determinants of behavioural intention: the personal or attitudinal component, and the social or normative component. The attitudinal component refers to a person's attitude towards performing the behaviour under consideration (Ajzen & Fishbein, 1980). Individuals' likelihood of performing a given behaviour will be strong if they hold a favourable attitude towards the performance of the behaviour. Fishbein (1993: xv) made a distinction between attitude towards an *object* (for example attitude towards shopping apps) and attitude towards a behaviour (for example attitude towards downloading shopping apps) in relation to an object. Attitude towards a behaviour is a much better predictor of that behaviour than the attitude towards the target of the behaviour (Fishbein, 1993: xv). Attitudes can be thought of as an overall evaluation (i.e. like or dislike; favourable or unfavourable) of an object (Hewstone, Stroebe & Jonas, 2015: 174).

Based on the above literature discussion and review of attitude as a salient factor in existing technology adoption theories and models, the research study extended the UTAUT2 Model by incorporating attitude towards the use of same-day delivery apps to ascertain its impact on

behavioural intention. The significance between attitude towards using technology and behavioural intention, as explored in the literature, is discussed next.

4.2.12.1 Attitude towards use and behavioural intention

Consumer attitudes play a crucial role in the behaviour of consumers (Makanyeza, 2014: 874). Thus, to adequately understand the behaviour of consumers, consumer attitudes must also be understood (Schiffman & Kanuk, 2004: 253). In the context of consumer behaviour, Schiffman and Kanuk (2004: 253) define consumer attitudes as "… the consistent tendency of consumers to behave, favourably or unfavourably, with regards to a specific product or brand". Scholars have noted that knowledge of consumer attitudes is critical in that it enables marketers to predict consumers' behaviours (Makanyeza, 2014: 874).

During the development of the UTAUT Model, Venkatesh et al. (2003: 455) considered the attitudinal construct to be spurious and, as a result, omitted it from the model (as discussed in section 4.3.12 above). Venkatesh et al. (2003: 455) postulated that effort expectancy and performance expectancy would provide more valuable insight into consumers' behavioural intention and expected a significant relationship between these constructs. Researchers have, with effort and performance expectancy included, investigated the influence of attitude towards users' intention to use technology, and found that attitude significantly influences behavioural intention (e.g. Hu & Zhang, 2016: 639; Jairak, Praneetpolgrang & Mekhabunchakij, 2009: 361; Nassuora, 2012: 1; Thomas et al., 2013: 71; Yeow, Yuen, Tong & Lim, 2008: 191; Yuen et al., 2010: 52).

The influence of the attitudinal construct on behavioural intention has further been tested in e-commerce and m-commerce research. During their investigation of students' likelihood of accepting m-learning, Jairak et al. (2009: 36) as well as Nassuora (2012: 1) found a significant positive relationship between attitude and behavioural intention. Thomas et al. (2013: 84) concur with these findings in their study explaining m-learning adoption in higher education in a developing country. They found that attitude significantly affects behavioural intention, even with the inclusion of the performance expectancy and effort expectancy constructs in the model. In exploring the factors influencing users' acceptance of online banking services in Australia, Yeow et al. (2008: 191) also found a positive correlation between attitude and behavioural intention. Attitude was reported as the most important factor in using Internet banking services (Yuen et al., 2010: 52) and Hu and Zhang (2016: 652) testify that students' attitudes towards m-library apps were the most significant predictor of behavioural intention.

Numerous studies, as evident from the above discussion, have found a strong relationship between attitude and behavioural intention, and consequently, the more positive the attitude individuals have towards certain behaviour, the more likely they are to form an intention to perform the behaviour (Al-Debei et al., 2013: 46; Heirman & Walrave, 2012: 614; Sanne & Wiese, 2018: 4). These findings contradict Venkatesh et al.'s assertion that the effect of attitude on behavioural intention is spurious. It is recommended that the UTAUT Model be further validated and replicated, as attitude was found to be a significant direct determinant in various UTAUT adoption studies (e.g. Oshlyansky et al., 2007: 1; Van Dijk et al., 2008: 385; Yuen et al., 2010: 52).

Research exploring the significance of attitude in the adoption of same-day delivery apps could not be found. A related study, however, explored five salient quality attributes associated with food delivery apps in consideration of their impact on users' attitudes and intention to continuously use them (Cho et al., 2018: 108). Cho et al. (2018: 113) posited that there is a positive relationship between attitude towards food delivery apps and the intention to continually use these apps, and report a significant and positive relationship. Lee et al. (2017: 1468) examined the relationship between the determinants that affect customers' use of food delivery apps by means of an extended TAM and found attitude towards the use of mobile delivery apps to positively affect the intention to use these apps. The results were supported by Shukla and Sharma (2018: 192), who also used TAM to examine the role of mobile technology in shopping for grocery items among consumers. Troise et al. (2021: 675) integrated the TAM and TPB frameworks to analyse the main drivers of users' intention to use food delivery apps and also support prior research that attitude is a significant predictor of behavioural intention.

The aforementioned research pertaining to related mobile apps, albeit limited, affirms attitude towards use as a strong predictor of behavioural intention and, as a result, supported the inclusion of the construct in the research study. The same theoretical stance was taken in the research study and the following is hypothesised:

Hypothesis 11: *There is a significant relationship between a positive attitude towards same-day delivery apps and consumers' behavioural intention to continue using same-day delivery apps.*

In sections 4.2.2 to 4.2.8 the relationships between the seven UTAUT2 Model constructs that underpin the research study were examined, namely performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, as well as price value. The relationships between four additional exogenous constructs, namely lifestyle compatibility,

perceived risk, perceived self-efficacy and attitude towards use, were then investigated in sections 4.2.9 to 4.2.12. The inclusion of these 11 independent constructs was affirmed with existing literature in the m-commerce and mobile app domain. Specific limitations in empirical evidence related to same-day delivery apps, especially in South Africa, warranted the insertion of the constructs in the conceptual model.

With the development of the initial UTAUT Model, Venkatesh et al. (2003: 470) specified that future studies might consider including additional theoretically motivated moderating constructs, different technological systems or devices, various user groups or other contexts and industries. Apart from investigating several UTAUT2 constructs in the context of same-day delivery apps, and within a South African context, two moderators were included. The theoretical motivation for including the moderators in the conceptual model is discussed in the next section.

4.2.13 THE MODERATING EFFECTS OF GENERATIONAL COHORT AND GENDER

A moderator is an independent construct that changes the strength of the correlation or relationship between an independent and dependent construct (Statistics Solutions, 2018). The moderator therefore influences or alters the strength or direction of the outcome between the independent and dependent constructs (Lewis-Beck, Bryman & Liao, 2004). Moderators are useful because they help explain the link between the independent and dependent constructs.

In Venkatesh et al.'s review (2012: 158) of the vast number of research undertakings utilising the UTAUT Model, they found that most studies using the UTAUT Model employed only a subset of the constructs, particularly by eliminating the moderators. Various researchers merely considered the direct influence of the independent constructs on the dependent construct, while discarding the impact of the moderator(s) on the particular relationship (Trojanowski & Kutak, 2017: 97-98). Although several studies failed to incorporate the moderators intended by Venkatesh et al. (2003), it is recommended that the UTAUT2 Model be tested with the inclusion of demographic factors (Ameen & Willis, 2018: 2; Trojanowski & Kutak, 2017: 97-98). Individuals are likely to differ substantially from each other in terms of their beliefs, values, perceptions and their understanding of different constructs (Trojanowski & Kutak, 2017: 97-98). Failure to examine the impact of heterogeneity may result in drawing inaccurate conclusions and formulating improper recommendations (Hair et al., 2012: 427; Trojanowski & Kutak, 2017: 97-98).

In the initial UTAUT Model, Venkatesh et al. (2003: 425) explored the moderating effect of gender, age, experience and voluntariness of use on the relationship between the independent constructs

and behavioural intention. In the UTAUT2 Model, Venkatesh et al. (2012: 159) omitted the 'voluntariness of use' moderator since consumers' behaviours are completely voluntary, and they are not obligated to use the technology in question, as would be the case in an organisational setting. The UTAUT2 Model therefore proposed the moderating effects of age, gender and experience. 'Experience', as a moderator, was excluded from the current research study, since (1) same-day delivery apps were still in their infancy in the South African market at the time of the study, and experience with these apps may have been limited, and (2) the data used in the research study was cross-sectional rather than longitudinal (Pradhina & Pillai, 2020: 104). 'Experience' is measured over a period of time and should be examined in a longitudinal study. The research study adopted generational cohort (age) and gender as moderators in exploring South African consumers' behavioural intention to continue using same-day delivery apps.

In evaluating how the UTAUT2 Model has been extended in various research studies, Venkatesh et al. (2016: 328) concluded that there is a gap in the literature on the effects of moderating factors, including age and gender. The same conclusion was reached by Dwivedi et al. (2017: 721), in particular, that the moderating effects of age have received relatively little attention in literature employing the UTAUT2 Model. Age and gender differences are key demographic variables that have a direct and moderating effect on behavioural intention and the adoption of new technological systems (Chung et al., 2010: 1675; Tarhini et al., 2014: 168; Venkatesh et al., 2003: 267; Wang et al., 2009: 97). Tarhini et al. (2014: 168) argue that the inclusion of age and gender as moderators would likely increase the explanatory power of technology acceptance and adoption behaviour research. Murugesh-Warren et al. (2015: 1) concur and state that demographic differences are often an important consideration in academic research, especially when exploring new technologies. Therefore, while most studies contribute to understanding the usefulness of the UTAUT2 Model in diverse contexts, there is still a need for a methodical analysis and theorising of the salient factors that would apply to the context of consumers' technology usage behaviours (Venkatesh et al., 2012: 158). As a result, the moderating effect of generational cohort (age) and gender was incorporated into the research study to examine the conceptual model in its entirety. The research study theorised the moderating effects of generational cohort and gender on consumers' behavioural intention to continue using same-day delivery apps, in an attempt to explore the impact of heterogeneity on the correlation between the independent constructs and the dependent construct.

Generational cohort and gender are contextualised from a South African perspective, and the significance of exploring generational cohort and gender differences in academic research is debated. Theoretical justification is then provided in support of the hypotheses for the inclusion of

exploring the interaction effect of generational cohort and gender differences on the relationship between the 11 identified independent constructs and consumers' behavioural intention to continue using same-day delivery apps in South Africa.

4.2.13.1 Generational cohorts in South Africa

The concept of generational cohorts endures as a key approach to classifying individuals based on shared historical and developmental contexts, offering a valuable distinction between the experiences of younger and older populations. As Mannheim (1952) described, generational cohorts (or age groups) share common understandings and unique reactions due to their distinct historical and developmental contexts (Deas, 2019). Those born within the same period experience similar formative events, shaping their perceptions, values, and attitudes (Deas, 2019). These shared experiences can lead generations to differ in their approaches and responses (Deas, 2019). Thus, generational cohort theory posits that social history and life experiences shape the attitudes and perceptions that distinguish successive generations (Van der Walt, Jonck & Sobayeni, 2019; Viljoen, Kruger & Saayman, 2018). To provide a theoretical comparison of age groups and differences based on their social histories and life experiences, age is classified according to generational cohorts.

Conversant to the work of Mannheim (1952), the generational cohort theory is emphasised by two elements that are central to the outset of a generation: a shared location in historic time and a distinctive awareness of the relevant historic period, shaped by events and experiences that are characteristic of that period which may have an impact on individual behaviour and cognition (in Van der Walt et al., 2019: 53). Generational cohorts are based on the premise that each cohort experiences shared and distinguishing circumstances and environmental forces that are prevalent during their formative years and, as a result, shape their behavioural patterns, beliefs, ideologies, expectations and views (Bevan-Dye, 2016: 5; Huang & Van der Veen, 2019: 7; Viljoen et al., 2018: 2). Accordingly, these unique differences develop distinct characteristics that can be used by marketers to define cohorts' preferences and behavioural patterns (Bevan-Dye, 2016: 5; Viljoen et al., 2018: 2).

Although a generational cohort is considered to span over a period of 10 to 25 years, it is established on six criteria and is shaped by historical events (McArthur-Grill, 2011: 7):

- A traumatic or formative social or economic event shapes the generation that lives through them, such as heroic leaders (e.g. Nelson Mandela), or experiences such as the rise of apartheid and South Africa's temporary isolation.
- A histrionic societal shift influences the distribution of resources, such as the rise of the Black middle class in South Africa.
- A privileged interval connecting a generation into a cycle of success and/or failure, for example a recession.
- The creation of sacred places that house a collective memory, for instance Sharpeville or Woodstock.
- Mentors whose work provided the stimulus for collective change, such as Nelson Mandela or Martin Luther King.
- Contributions of people who support each other, for instance technology innovators, such as Steve Jobs and Bill Gates in the Generation X era.

In most Western countries, especially in the USA, six major generational cohorts are identified: the Silent Generation or Traditionalists (born before 1945), Baby Boomers (1946 – 1964), Generation X (1965 – 1980), Generation Y (1981 – 1990), Generation Z (1991 – 2012) and Generation Alpha (2013 – mid-2020s) (Huang & Van der Veen, 2019: 7). Padayachee (2017: 60), however, argues that Westernised definitions of generational cohorts may not be applicable in the South African context as the events that define a cohort in South Africa differ largely from Western countries. South Africa's history was defined by several events and profound political and societal transformations that demarcated each generation, such as the Sharpeville Massacre (1960), the Soweto Uprising (1976) and the banning of the African National Congress (1960 – 1990), among others (Viljoen et al., 2018: 2).

Although there is a lack of consensus about the generational cohorts in South Africa, Viljoen et al. (2018: 5) present the defining moments in South African history compared to Western societies. They argue that while global events shape the formation of cohorts, national events contribute to generational consciousness. National events, such as apartheid, the Border War, Sharpeville Massacre, Rivonia trials, economic sanctions, Internet connectivity and democracy, influenced the ideas, thoughts, beliefs and behaviours of people during those times (Viljoen et al., 2018: 5). These events resulted in a different set of generational cohorts compared to those acknowledged in Western societies, as presented in Table 4.1.

Table 4.1: Comparative summary of generational cohorts according to country and national events

Generation	South Africa	USA	Europe/UK	Global and national events
The Silent Generation/ Traditionalists	1930 – 1949	1923 – 1942	1918 – 1945	Great Depression (1929 – 1939) World War II (1939 – 1945) Apartheid (1948 – 1991)
Baby Boomers	1950 – 1969	1943 – 1962	1946 – 1965	Sharpeville Massacre (1960) South African Republic (1961) Rivonia trials (1963) Imprisonment of Nelson Mandela (1964) Border War (1966 – 1989)
Generation X	1970 – 1989	1963 – 1983	1966 – 1984	South Africa's removal from United Nations (1974) South Africa's first television broadcast (1976) Soweto uprising (1976) South Africa's economic sanctions (1985)
Generation Y (Millennials)	1990 – 2000	1984 – 2001	1985 – 2001	Apartheid negotiations (1990) Personal Internet (1992) South African democracy (1994) Rugby World Cup (1995)
Generation Z (Zoomers)	2001 – 2015	2002 – 2012	2002 – 2012	Climate change Great Recession (late 2000s) War on terror
Generation Alpha (Alphas)	2016 – 2020	2013 – 2020	2013 – 2020	COVID-19 pandemic (2019) Terrorism and war Social networking Gender equality

Source: Cawood (2015); Lerm (2022); McArthur-Grill (2011: 10); Tanner (2022); Van der Walt et al. (2019: 53); Viljoen et al. (2018: 5)

Baby Boomers in South Africa were defined by the Black Consciousness Movement, an anti-apartheid movement that emerged in South Africa in the mid-1960s with the jailing and banning of the African National Congress (ANC) and Pan Africanist Congress leadership after the Sharpeville Massacre in 1960 (Bevan-Dye, 2016: 12). Generation X was marked by apartheid, political violence, economic instability and sanctions, whereas Generation Y grew up during the transitional post-apartheid era with more education and employment opportunities (Bevan-Dye, 2016: 12; Padayachee, 2017: 60). Generation Z, also known as the iGeneration or Zoomers, would be characterised by the born-free generation in South Africa, who were born after the dawn of democracy in South Africa (Padayachee, 2017: 60). Members of Generation Z are characterised as being more technologically innate and able to use multiple technological systems and devices (Dobrowolski, Drozdowski & Panait, 2022: 2). Lastly, Generation Alphas have their own mobile

devices, instant Internet access, social media, the gamification of education and podcasts (Roberts, 2023).

Table 4.2 provides a classification of the six South African age cohorts based on Statistics South Africa's 2021 mid-year data.

Table 4.2: Classification of the six generational cohorts in South Africa (2021)

Silent Generation	Baby Boomers	Generation X	Generation Y	Generation Z	Generation Alpha
1930 – 1949	1950 – 1969	1970 – 1989	1990 – 2000	2001 – 2015	2016 – 2020
72 years and older	52 – 71 years	32 – 51 years	21 – 31 years	6 – 20 years	1 – 5 years
±2.27 million citizens	±8.11 million citizens	±17.75 million citizens	±10.1 million citizens	±16.24 million citizens	±5.71 million citizens

Note: Data for the research study were collected during 2021, and therefore the 2021 population statistics are reported.

Source: Statistics South Africa (2021: 19)

Although cognisance is taken of the different generational cohorts discussed in the literature, the Silent Generation, Generation Alpha and a portion of the Generation Z population were not included in the research study. The rationale being that the sample population was drawn from South African consumers who were between the ages of 18 and 65 years. Because the Silent Generation and Generation Alphas were therefore not included in the research study, these cohorts will not be discussed further. Generation Z consumers, born between 2001 and 2003, who would have been 18 years of age at the time of data collection, were included in the study. The pioneering technology of each of the four cohorts included in the research study, as well as the generation's attitude and adoption behaviour of new technologies, will be explored in the next section.

4.2.13.2 Generational cohorts' characteristics of technology adoption

When defining emerging trends and establishing patterns among individuals and consumer groups, age can be a valuable instrument. The introduction of various technologies shapes the behaviours of individuals born in a specific era, and age is one of the factors that may affect individuals' intention to use an information system (Gafni & Geri, 2013: 20; Venkatesh et al., 2012: 159). While many researchers claim that younger generational cohorts are more adaptable to new technologies, the proclivity to use various new technologies and devices may be influenced by

cultural differences. As a result, it may be more appropriate to cluster age groups according to the defining moments or events that shaped each generational cohort (Gafni & Geri, 2013: 20).

- **Baby Boomers (1950 – 1969)**

The term 'Baby Boomers', who were born between 1950 and 1969, originated from the period after World War II with war veterans thankful to be alive. After World War II, many countries experienced a spike in the birth rate as Baby Boomers slowly recovered from the economic hardships experienced during the war and Great Depression (Deas, 2019: 242). In South Africa, the Baby Boomers redefined traditional values and view themselves as a hard-working generation (Morris, 2018). They are characterised as work-centric and goal-oriented, independent, a sceptic of authority, social reformers, adventure seekers, competitive in the workplace and lifelong learners (Huyler & Ciocca, n.d.: 96). Baby Boomers were raised in a relatively positive era characterised by opportunities for growth and development (Deas, 2019: 242).

Baby Boomers were the first generation to have access to television and their preferred way of communicating is by telephone. They rely on postal and courier services and view education as a right, not a privilege (Padayachee, 2017: 61). Baby Boomers have greater access to the Internet and their Internet usage patterns are similar to those of younger generations (Kumar & Lim, 2008: 570).

A common misconception of Baby Boomers is that they lack understanding of the use of technology and that they fail to use it effectively (Huyler & Ciocca, n.d.: 96). Kumar and Lim (2008: 570) assert that Baby Boomers are experienced users of modern technologies as they have witnessed numerous technology changes throughout their lifetime. They are considered early adopters of information technology (Linnes & Metcalf, 2017: 15) and spend most of their disposable income on technological gadgets and participating in online shopping (Joubert, 2013: 44).

In a study aimed at determining Baby Boomers' perceptions of social networking sites in South Africa, it was discovered that they value having access to the latest information; however, security and privacy concerns, as well as factors such as a lack of time and prohibitive costs were cited as barriers (Nyemba, Mukwasi, Mhakure, Mosiane & Chigona, 2011: 701). Although Baby Boomers are technologically advanced and may be comfortable using mobile phones, their intentions to use mobile devices and services are vastly different from those of Generation X and Y (Kumar & Lim,

2008: 570). Typically, Baby Boomers will use mobile phones for making voice calls, but use data services sparsely (Kumar & Lim, 2008: 570).

- **Generation X (1970 – 1989)**

Born between 1970 and 1989, Generation X-ers did not experience the same strong economic conditions as Baby Boomers. They are considered to be one of the most highly educated generations, characterised by scepticism, pragmatism and an attitude of risk avoidance (Calvo-Porral & Pesqueira-Sanchez, 2019: 2756). Also known as the Latchkey Generation, Generation X members value a balanced lifestyle, personal responsibility, multiculturism and global thinking (Ling, D'Alessandro & Winzar, 2015: 85). Members of Generation X witnessed the collapse of the Soviet Union, epidemic outbreaks such as HIV/Aids and the introduction of personal computers, cellphones and the Internet (Deas, 2019: 243).

In South Africa, individuals belonging to Generation X include those who are old enough to remember apartheid and be judged by history to have been part of it, but not quite old enough to be involved in any struggle against apartheid (Joubert, 2013: 45). These consumers were at the forefront of a historic evolution that led to a democratic South Africa and refused to conform to be marginalised. Generation X is characterised and remembered for their unequivocal stance against apartheid. Despite their scepticism and apprehension of new technology, Generation X-ers are the most enthusiastic adopters of technology (Mosupyoe, 2014: 55).

Generation X-ers are described as digital immigrants, as they were not brought up with the Internet and digital technologies, but later in life adopted many new technologies (Calvo-Porral & Pesqueira-Sanchez, 2019: 2756; Linnes & Metcalf, 2017: 15). Generation X-ers rely on personal computers, the Internet, e-mail and mobile phones to communicate (Padayachee, 2017: 62). With respect to technology, individuals belonging to this generation are expected to be well acquainted with cellphones and social media (Duh & Struwig, 2015: 97).

- **Generation Y (1990 – 2000)**

Generation Y members, also widely referred to as Millennials, were born between 1990 and the turn of the century. Millennials have seen the rise and expansion of the Internet, are environmentally conscious, accepting of social media, economic liberty and an upsurge in terrorism (Deas, 2019: 243). Commonly raised by overprotective parents, Millennials' core values

include optimism, light-heartedness, driven, being risk-takers as well as being goal- and future-oriented and focused on their civil duties (Deas, 2019: 243; Linnes & Metcalf, 2017: 15).

In South Africa, Generation Y members are the first generation to grow up in the post-apartheid era. Many Generation Y-ers became the first in their families to attend multiracial schools and interact with various racial groups (Bevan-Dye, Garnett & De Klerk, 2012: 5582). South African Millennials grew up in times of major transition, with profound social impacts, accelerating urbanisation and expanding globalisation (Mosupyoe, 2014: 52).

Being the first high-tech generation and born into the age of technology, which is defined by substantial computer and mobile usage as well as relentless communication via social media, Millennials are also known as digital natives (Padayachee, 2017: 62). As a result, they are considered to be more sophisticated, technologically literate and techno-savvy (Calvo-Porral & Pesqueira-Sanchez, 2019: 2756; Joubert, 2013: 47). Millennials integrate technology into their daily lives and are early adopters of new technologies (Calvo-Porral & Pesqueira-Sanchez, 2019: 2757; Kumar & Lim, 2008: 570). Members of Generation Y are considered to be extensive users of the Internet, mobile technology and services, connectivity, interactive media and social networking (Calvo-Porral & Pesqueira-Sanchez, 2019: 2757). They have also been described as individuals who use technology to stay connected on social networking sites and create and share content through various social media platforms (Noble, Haytko & Phillips, 2009: 624). As a result, Millennials are strongly influenced by social media (Padayachee, 2017: 62).

According to Jain and Viswanathan (2015: 296), Millennials spend more time on digital platforms, such as smartphones and tablets, and their mobile phones are symbols of their uniqueness. Millennials tend to regularly download new mobile apps and use mobile apps for entertainment, relaxation as well as information and educational purposes (Jain & Viswanathan, 2015: 296). They are technologically savvy, constantly wired, plugged in and connected (Pelet & Lecat, 2014: 189). Technology has significantly influenced Millennials' behaviours, their way of thinking and their learning processes as they perceive information and communication technologies more positively compared to preceding generation groups (Calvo-Porral & Pesqueira-Sanchez, 2019: 2757).

In South Africa, Generation Y comprises approximately 10 million South African citizens (Statistics South Africa, 2021: 19), and was the first generation born into the age of mobile phones, convergent technologies and multiplatform media (Bevan-Dye et al., 2012: 5581). Millennials grew up in a multimedia-rich world that allows constant access to instantaneous global news and information, virtual social networking (e.g. Facebook), virtual social reporting (e.g. Twitter) and

virtual social media (e.g. YouTube) (Bevan-Dye et al., 2012: 5581). Chalomba (2016: 25) points out that Millennials are being targeted by marketers as they are extensive users of mobile phones and rely on mobile apps to obtain brand information in many aspects of their lives. Millennials are seen as the future market for the global economy since they have growing purchasing power (Chalomba, 2016: 25).

- **Generation Z (2001 – 2015)**

South Africans born between 2001 and 2015 are referred to as Generation Z. Due to their reliance on the use of smartphones, tablets and wearables (e.g. iWatch), and their constant yearning for new innovative technology and devices, they are also referred to as the iGeneration (Padayachee, 2017: 62). Members belonging to Generation Z are highly connected as they live in an age of high-tech communication, technology-driven lifestyles and prolific use of social media. Generation Z members are characterised as being more technologically innate, able to use multiple screens simultaneously, thinking in 4D, active volunteers, racially and gender blended, believe in togetherness, communicate with images, have a collective consciousness, want to make things and are more future-focused (Maseko, 2015). Innovative products launched during this period and with which they are associated include Google Glasses, graphene, nano-computing, 3D printing and driverless cars (Linnes & Metcalf, 2017: 15). Members of Generation Z communicate mainly by hand-held communication devices and prefer FaceTime, Twitter, Tik Tok and Snapchat compared to frontal communication (Linnes & Metcalf, 2017: 15). The most popular mobile apps downloaded by Generation Z, according to Axcell (2017: 47), are messaging, social media, music and gaming apps, and apps that are used the least include dating, fashion, bargain/coupon, retail and food-related apps.

In South Africa, Generation Z is commonly referred to as the Born Free generation, since they were born after the country attained democracy in 1994 and after the apartheid era. There is no denying that Born Frees have grown up in a time with its own economic and political turmoil, with issues such as unemployment, poor education levels, crime, questionable political leadership, global warming and recovery from the most recent economic depression (Leshilo, 2015).

Table 4.3 provides a matrix of the technological characteristics of each generation discussed above.

Table 4.3: Matrix of generational and technological traits

Generation	Characteristics	Technology context	Technology preferences
Baby Boomers	Digital immigrants	Television, computers, modems	Print, snail mail, face-to-face dialogue, online tools and resources
Generation X	Digital immigrants Digital adopters	Overwhelming media, digital and satellite television, mobile phones, palm pilots, personal computers	Online, some face-to-face meetings, games, technological interaction
Generation Y	Digital natives Thrive on communication via social sharing, e-mail and SMS	Mobile technologies Access to instant global news and information Virtual social networking, reporting and social media sites	Online, wired, seamlessly connected through technology
Generation Z	Superficial extraverts – socialisation is done completely online	Ubiquitous use of personal computers, tablets and smartphones	Online, texting, YouTube, apps and social networking

Source: Padayachee (2017: 63)

In the next section, the prolific use of gender in academic research will be discussed.

4.2.13.3 Gender differences

Gender has become the most researched demographic variable in studies involving factors of intention to adopt new technologies (Rudito, 2010: 90), and research has suggested that it plays a vital role in predicting usage behaviour in the domain of information systems research (e.g., He & Freeman, 2009: 1; Tarhini et al., 2014: 163; Venkatesh et al., 2003: 450; Wang et al., 2009: 111). According to Rudito (2010: 90), research has shown an increased interest in examining gender as a moderator in an effort to better understand its impact on adoption or acceptance models, because men and women react differently to new technologies.

Several studies have found that there are differences between males and females in their technology-related variables, including adoption or intention behaviour (Morris & Venkatesh, 2000: 397). Gender has become the most researched demographic variable in the studies involving antecedents of intention to adopt new technology (see Rudito, 2010: 90). It has largely been used in previous studies as a moderating factor to be investigated for its impact on adoption or acceptance models (Rudito, 2010: 90). Different responses by men and women towards technologies were believed to be the reason why many researchers were interested in conducting those studies. Generally, the literature reports that males have more favourable attitudes towards

technologies than their female counterparts, and females commonly experience heightened computer anxiety and more negative perceptions than males (Altawallbeh, Soon, Thiam & Alshourah, 2015: 47). Rudito (2010: 90) claims that the role of gender as a moderator in acceptance models is substantial, and therefore should be included in any model adopted for further investigation purposes.

It is clear that gender differences have the ability to change the relationship between the independent constructs and the dependent construct. Consequently, the aim of the research study was to investigate the moderating impact of gender on consumers' behavioural intention to continue using same-day delivery apps.

The relevance and significance of age and gender preferences, as well as the ways in which they differ from one another, are discussed in the following section.

4.2.13.4 The moderating effect of generational cohort and gender differences on consumers' behavioural intention

In the development of the UTAUT2 Model, Venkatesh et al. (2003: 427) explored the moderating effect of age and gender differences as well as past experience on consumers' behavioural intention to use new technology. 'Experience' was omitted from the conceptual model because, at the time this research study was conducted, same-day delivery apps were still in their developmental phase, and the adoption of same-day delivery apps has only recently emerged as a result of the COVID-19 pandemic. Venkatesh et al. (2003: 437) recommend that experience with a new technology be tracked over various stages over a period of time (in a longitudinal study). Due to the nature of this current cross-sectional research study, experience could not be monitored over a period of time as experience with same-day delivery apps increased. It is recommended that future research undertakings explore the moderating effect of experience on consumers' behavioural intention to continue using same-day delivery apps in a longitudinal study.

The succeeding section highlights extant literature validating the significance of generational cohort and gender differences in the adoption of new technology and their moderating effect on behavioural intention. Research pertaining specifically to the moderating effects of generational cohort and gender on behavioural intention to continue using same-day delivery apps, specifically, could not be found. Therefore, the significance of generational cohort and gender as moderators in related adoption and intention behaviour research is reported to justify the implication and affirm its inclusion in the conceptual model.

Furthermore, due to a scarcity of studies examining the moderating effect of the various generational cohorts on the UTAUT2 model and behavioural intention, particularly within a South African context, this research takes a broader perspective. Prior research where participants are broadly categorised into “young” and “old” age groups are explored. Although this approach simplifies generational complexities, it emphasises the continued value of exploring age-based moderators in technology adoption research.

The moderating effect of generational cohort and gender on the relationship between the seven UTAUT2 constructs and behavioural intention will be explored first.

4.2.13.4.1 The moderating effect of generational cohort and gender on the relationship between the UTAUT2 constructs and behavioural intention

As stated earlier, previous research studies did not apply the complete UTAUT2 Model as intended by Venkatesh et al. (2012), as many employed only a subset of the model, typically omitting the moderators. A potential reason for excluding the moderators might be that there is no variation in the moderators in the context of adoption and use behaviours. Research on technology acceptance and adoption behaviour would likely have more explanatory power if the moderators were included. The effects of heterogeneity were therefore investigated to develop more reliable recommendations.

The moderating influence of generational cohort and gender on the relationship between the UTAUT2 constructs (performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value) and behavioural intention is discussed below, in contrast to what has been found in previous studies.

- **Performance expectancy**

Males are often more task-oriented, according to Venkatesh et al. (2003: 449), and therefore performance expectancies that concentrate on task successes are likely to be important, particularly to men. Venkatesh et al. (2003: 450) further postulate that performance expectancy is particularly strong for younger men in an organisational context since younger workers tend to place more emphasis on extrinsic motivation. In the e-commerce domain, these findings were corroborated by Ameen and Willis (2018: 16), Chang, Liu, Huang and Hsieh (2019: 1), Khechine, Lakhal, Pascot and Bytha (2014: 44), Nunes et al. (2019: 4) and Wang and Wang (2010: 421). Mobile Internet adoption was examined by Wang and Wang (2010: 421), who found performance

expectancy to be moderated by gender, where the intention was stronger for men than for women. A positive effect of performance expectancy on the intention to use an e-learning platform was moderated by age, such that the effect was more substantial for younger students (Khechine et al., 2014: 44).

In more recent studies, Ameen and Willis (2018: 16) found that the effects of performance expectancy on consumers' intention to adopt smartphones were stronger among the older age group. Chang et al. (2019: 14) explored the drivers of online booking intentions and report that the relationship between performance expectancy and behavioural intention was moderated by gender, where the intention was greater for men than for women. Performance expectancy was furthermore positively associated with the behavioural intention to use m-health apps in both younger and older participants, with a slightly stronger effect for younger participants (Nunes et al., 2019: 4). These researchers posit that more mature individuals, who likely have a family, value technology that is task-directed and offers certain benefits. Okonkwo (2019: 49) states that men seem to be more task-oriented than women and mobile apps are typically inspired by goal realisation.

The above arguments affirm the hypothesis adopted for the research study that the relationship between performance expectancy and behavioural intention will be moderated by generational cohort (age) and gender.

- **Effort expectancy**

In the development of the UTAUT Model, Venkatesh et al. (2003: 468) hypothesised that the influence of effort expectancy will be moderated by age and gender, such that the effect will be stronger for younger women. The results verified that the effect of older women was a stronger predictor between effort expectancy and behavioural intention. Prior research supports the notion that effort expectancy will be a stronger determinant for women and older individuals (Venkatesh & Morris, 2000: 121). The argument that effort expectancy will be a stronger predictor for women is based on the premise that men are more task-oriented, and women will adopt and use a technology if it requires less effort to operate (Onwona-Agyeman, 2019: 7). It is furthermore argued that when technology is easy to use, older people will be more inclined to adopt it (Onwona-Agyeman, 2019: 7).

Although contradictory empirical evidence is found in the literature, Venkatesh et al.'s proposition (2003: 468) is widely supported in m-commerce research. For example, the factors that influence

consumers' intention to use mobile apps were examined by Kang (2014: 360). Kang's analysis (2014: 373) found that only gender moderated the relationship between effort expectancy and continuance intention, implying that women were more likely than men to prefer ease of use for continuance intention. The effect of different business models on the adoption of a mobile gaming app was explored by Van Katwijk (2014: 38), who discovered that the strength of the relationship between effort expectancy and behavioural intention increases as consumers get older. Correspondingly, Ameen and Willis' study (2018: 16) analysed the moderating effect of age on smartphone adoption. They report that effort expectancy is more significant among older users as they tend to prefer tasks that require little effort and are easy to do. Similarly, Nunes et al. (2019: 7) report effort expectancy to be moderated by age and gender, but in their study on m-health app adoption behaviours, effort expectancy was particularly relevant to older men, not women, as proposed by Venkatesh et al. (2003: 468).

The same premise was assumed in this current research study, namely that the relationship between effort expectancy and behavioural intention will be moderated by generational cohort (age) and gender.

- **Facilitating conditions**

In the context of consumer adoption behaviour, Venkatesh et al. (2012: 163) expected that age and gender will moderate the effect of facilitating conditions on behavioural intention, such that the effect will be stronger among older women. Venkatesh et al. (2012: 162) argued that older consumers have more difficulty in processing new or intricate information, which affects their learning of new technologies. This problem may be ascribed to the decline in cognitive and memory capabilities associated with the ageing process. Therefore, when compared to younger consumers, older consumers place greater emphasis on the availability of adequate support. Moreover, men are willing to spend more effort to overcome limitations and complications to pursue their goals, whereas women are inclined to focus more on the magnitude of effort required and the process of achieving their goals. As a result, men tend to rely less on facilitating conditions when considering the use of new technologies.

Contradictory to Venkatesh et al. (2012: 163), many research undertakings in the context of e-commerce and m-commerce yielded different results. Where Venkatesh et al. (2012: 163) posit that the relationship will be more salient for older women, several researchers found the opposite effect of gender on the relationship between facilitating conditions and behavioural intention. Curtis et al. (2010: 91) discovered that men place more emphasis on facilitating conditions than their

female counterparts in the adoption of social media for public relations by non-profit organisations. These findings were substantiated by Maduku (2015: 11), who explored the role of gender differences in the adoption of e-books and found that males had a stronger effect on facilitating conditions than females, suggesting that females have different beliefs regarding the availability of infrastructure and personal support available to them in using e-books (Maduku, 2015: 11). In a more recent study, Nunes et al. (2019: 4) discovered that the effect of facilitating conditions on the acceptance of mobile health apps was higher for men than for women. Contrary to these findings, Yapp et al. (2018: 117, 119) found that facilitating conditions are a key determinant in the adoption of on-demand service apps and contend that females invest more of their resources in time, money and effort when it comes to using technology-related products or services. These findings suggest that the perceived availability of resources and support is a relevant condition for men to be interested in using new technology, such as same-day delivery apps.

Research supports Venkatesh et al.'s notion (2012: 163) that the relationship between facilitating conditions and behavioural intention will be more salient for older consumers. Researchers supporting the notion include Abdulwahab and Zulkhairi (2012: 97) and Khechine et al. (2014: 45). Abdulwahab and Zulkhairi found that the effect of age on facilitating conditions with regard to users' acceptance of telecommunication centres was stronger in older users than younger ones. Khechine et al. concur as they too found that the effect of facilitating conditions on the intention to use a webinar system was statistically significant when moderated by age, such that the effect was more relevant to older students.

Based on the preceding discussion, the opinion is held that the relationship between facilitating conditions and behavioural intention will be moderated by generational cohort (age) and gender.

- **Social influence**

From an organisational perspective, Venkatesh et al. (2003: 453) argue that affirmation needs increase with age, suggesting that older workers are more likely to place increased salience on social influence. They furthermore argue that women tend to be more sensitive to others' opinions and prefer social interactions when forming intentions to use new technology. Researchers therefore suggest that social influences are more relevant to women than to men (Lee et al., 2017: 566; Venkatesh et al., 2003: 453). As a result, in the development of the UTAUT Model, Venkatesh et al. (2003: 468) theorised and verified that the impact of social influences on behavioural intention will be moderated by age and gender, such that the effect will be stronger for older women.

Yet again, opposing empirical findings are reported extensively in the literature. Venkatesh et al.'s hypothesis (2003: 453) that the effect of social influence on behavioural intention will be stronger for older women is nevertheless supported in many m-commerce studies. Research indicates that women have higher levels of perceived risk regarding online shopping than men, and therefore recommendations from friends and family have a greater effect on a women's intention to shop online (Lian & Yen, 2014: 137). Yapp et al. (2018: 117), however, report that social influence is equally important to male and female consumers in adopting on-demand service apps. In exploring the social influence on how individuals were introduced to new apps, all the respondents agreed to peer influence being a driver for use of the apps (Arora, Malik & Chawla, 2020: 191). It was reported that, in the case of Generation X customers, social influence was limited to peer influence only, whereas Generation Y customers were influenced by both peer and mass influencers (Arora et al., 2020: 191), suggesting that social influences were a strong predictor for both older and younger consumers. Lian and Yen (2014: 137) found the major online driving force for older adults to be social influence. Older individuals are more likely to rely on social support when they have less experience with technology (Onwona-Agyman, 2019: 7). In a study utilising the UTAUT2 constructs to explore students' intention to use social networking sites, Liu, Chang, Huang and Chang (2016: 793) revealed that male students are subject to less influence on the relationship between social influence and behaviour intention. These findings validate Abdulwahab and Zulkhairi's results (2012: 97), which also revealed that the effect of social influence on behavioural intention was stronger for females than males in the adoption of telecommunication centres.

The same significant interaction effect between social influence and behavioural intention was assumed in this study.

- **Hedonic motivation**

The effect of hedonic motivation on behavioural intention is expected to be moderated by generational cohort and gender due to differences in consumers' reception of new technology, their search for novelty and their perceptions of the novelty of a particular technology. It is argued that younger men exhibit a greater tendency to seek novelty and innovation, and therefore Venkatesh et al. (2012: 163) theorised and validated that the effects between hedonic motivation and behavioural intention will be stronger for younger men in their adoption of new technology.

Limited, and contradictory, findings supporting Venkatesh et al.'s notion (2012: 163) could be found in previous research studies. One study discovered that younger people are more likely to

find mobile shopping to be entertaining and fun, and therefore it is argued that younger people place more value on hedonic motivations (Trojanowski & Kutak, 2017: 109). Lian and Yen (2014: 134) also state that the elderly, who have a higher tendency towards nostalgia, are less likely to use the Internet or shop online, and they get less enjoyment from it. Moreover, Trojanowski and Kutak (2017: 109) state that older people tend to use mobile phones for more pragmatic purposes, whereas younger people exhibit a greater propensity to seek novelty. Ansari and Farooqi (2017: 48) suggest that females place more emphasis on hedonic motivations because they tend to enjoy mobile shopping more than their male counterparts. Sohn, Schulte and Seegebarth (2014: 36) claim that men generally download mobile apps that are utilitarian in nature (task-directed) as opposed to hedonic apps that are perceived to be enjoyable. However, Yapp et al. (2018: 117) report that females place more importance on hedonic motivation in the acceptance of on-demand service apps than male consumers. Several researchers also rejected Venkatesh et al.'s proposition (2012: 163), reporting that age and gender do not significantly moderate the relationship between hedonic motivation and behavioural intention (e.g. Dutta & Shivani, 2020: 696; Palau-Saumell et al., 2019: 16; Yuan et al., 2015: 737).

Due to the restricted and conflicting empirical evidence available in the literature, it was imperative to explore the interaction effect of generational cohort (age) and gender on the relationship between hedonic motivation and behavioural intention to improve the predictive and explanatory power of the conceptual model and contribute to the body of knowledge on adoption behaviour research. It was therefore postulated that the relationship between hedonic motivation and behavioural intention will be moderated by generational cohort (age) and gender.

- **Habit**

The literature suggests that older people experience more difficulty in acquiring new skills (Trojanowski & Kutak, 2017: 100). It is difficult for older people to change their old habits when they have learnt to use technology in a specific way over a period of time. They often rely on repetitive actions and revert to their habits more often than younger consumers (Venkatesh et al., 2012: 165). The literature furthermore suggests that women display more sensitivity to details than men when making decisions, primarily because men tend to process stimuli and information in a schema-based manner while overlooking unfamiliar information, whereas women process information in a sequential and detailed manner. Thus, women are more sensitive to new stimuli and changes in the environment and, as a result, their purchasing intention is less affected by habit (Trojanowski & Kutak, 2017: 100; Venkatesh et al., 2012: 165). Venkatesh et al. (2012: 165),

in the development of the UTAUT2 Model, hypothesised and confirmed that age and gender moderate the effect of habit on behavioural intention, such that the effect is stronger for older men.

Although contradictory findings are reported in the literature, a few recent studies in e-commerce corroborate Venkatesh et al.'s suggestion (2012: 165) that the effect between habit and behavioural intention will be stronger for older men. One such study conducted by Huang (2018: 4) applied the UTAUT2 Model to explore the influence of the UTAUT2 predictors on students' intention to use social media. Huang (2018: 143) reveals that habit is a significant predictor of behavioural intention towards social media usage, although the effect is slightly stronger for female students. Similarly, Trojanowski and Kutak (2017: 110) found the impact of habit on the intention to use a mobile phone for purchases is stronger for older men. The factors influencing consumers' mobile shopping adoption intention were explored by Marriott and McLean (2019: 1) through the development of the mUTAUT Model incorporating more consumer-oriented constructs. They discovered that the structural relationship between habit and intention is moderated by age within mUTAUT, in finding older consumers being more influenced than younger consumers. Ameen and Willis (2018: 7) expected the effect between habit and smartphone adoption to be stronger among older individuals, since they develop habits relating to the use of technology faster than younger people do; however, their study revealed no significant moderating effect. It is argued that younger people are used to instantaneous rewards and feedback and are therefore less likely to react on impulse (Van Deursen, Bolle, Hegner & Kommers, 2015: 417). The aforementioned empirical findings affirm that the effect of habit will be more salient for older consumers in adopting consumer technology.

Empirical evidence pertaining to the influence of gender and the effect between habit and behavioural intention in m-commerce research was scarce. Only one study could be found corroborating Venkatesh et al.'s proposition (2012: 165). Trojanowski and Kutak (2017: 110) found the impact of habit on the intention to use a mobile phone for purchases is stronger for men than women. Other studies that were found all report an insignificant effect of gender on the relationship between habit and behavioural intention (e.g. Chang et al., 2019: 12; Hew et al., 2015: 1269; Isa & Wong, 2015: 392; Palau-Saumell et al., 2019: 1; Yuan et al., 2015: 737).

Due to the lack of consensus regarding the moderating effect of age and gender, and the lack of research specifically on the use of mobile apps, further debate in this area is warranted. The assumption is made that the relationship between habit and behavioural intention will be influenced by generational cohort (age) and gender.

- **Price value**

According to research, men and women often take on various social roles and display different behaviours. Men are generally more modest and independent, and make decisions based on selected information and heuristics, whereas women are more reliant and supportive, considering more detail. As a result, women are expected to pay more attention to the price of products and services and are generally more price-conscious than men. Additionally, women are stereotypically more involved in the purchasing process and therefore more accountable and cautious with money than men (Venkatesh et al., 2012: 163). Moreover, Venkatesh et al. (2012: 163) claim that older women are more inclined to be price sensitive because of their social role as gatekeepers of the family's expenses, implying that the monetary value of products and services is more important to older women. Venkatesh et al. (2012: 163) therefore hypothesised and confirmed that the effect of price value on behavioural intention will be stronger among older women.

In general, past research mostly reported that, due to the traditional role of being the main household provider and value-for-money option seekers, women are more price sensitive and more responsive to price changes than men (Diaz & Cataluña, 2011: 373; Mihić & Milaković, 2017: 1304; Mitchell, 2012; Ramprabha, 2017: 58). Scholars have argued that women are more likely to be deal-prone than their male counterparts (DelVecchio, 2005: 388; Tjarks, 2018: 85), whereas Sututemiz and Saygili (2018: 224) report that both males and females declare price as one of the main advantages of online shopping. In exploring the adoption of smartphones in the UAE, Ameen and Willis (2018: 16) discovered that price value had a significant effect on behavioural intention in both age groups, but that price value was more important among the older age group.

Although research pertaining specifically to the behavioural intention to continue using same-day delivery apps was limited, and while conflicting findings were apparent in the literature, exploring age and gender differences would ultimately increase the predictive and explanatory power of the UTAUT2 Model and contribute towards understanding behavioural intentions among consumers. The moderating effects of generational cohort (age) and gender between the UTAUT2 constructs and behavioural intention were therefore investigated in the research study to determine their significance in the South African context.

The next section provides a proclamation of the moderating effects of generational cohort and gender between the four additional exogenous mechanisms included in the conceptual model

(lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use) and behavioural intention.

4.2.13.4.2 The moderating effect of generational cohort and gender on the relationship between lifestyle compatibility and behavioural intention

As discussed in section 4.2.9, personal factors, such as a consumer's lifestyle and preferences, influence their adoption of new technology. It is reasoned that if technology, such as a mobile shopping app, is compatible with a consumer's lifestyle and aligns with their routine, they will be persuaded to use the technology. Individuals are increasingly turning to technology to ease the pressure of the fast-paced lives they are leading, which involve juggling a full-time job, the family and household duties, among other things. It is not surprising that different technologies will be better suited to various age groups and genders given the varied life cycle stages and stereotypical roles in the family life cycle.

Previous research has focused mainly on the interaction effects of gender in the adoption of innovative technology in the banking industry (Chawla & Joshi, 2020: 483; Kieran, n.d.: 65; Yang et al., 2021: 14), whereas research in the mobile retail industry is scant. Kieran (n.d.: 65) assessed the key factors that influence the adoption of mobile banking apps and discovered that a person's lifestyle is affected by gender, such that mobile banking apps are more compatible with a woman's lifestyle than with a man's. Chawla and Joshi (2020: 483) examined the factors that influence the attitude and behavioural intention towards mobile wallet adoption. Their empirical findings reveal that the impact between lifestyle compatibility and behavioural intention is stronger for males than for females (Chawla & Joshi, 2020: 495). In a similar study, Yang et al. (2021: 1) studied the factors that influence the intention and adoption to use an e-wallet by extending the UTAUT Model. They report that females' attitude towards the adoption of e-wallets significantly affects how they spend their e-money to purchase products, inferring that the relationship between lifestyle compatibility and behavioural intention is more pertinent to women than men. These studies, however, explored the adoption of online banking services, which could yield conflicting results due to men conducting more e-commerce activities (Faqih & Jaradat, 2015: 40) and are therefore more prone to use mobile banking services for convenience and ease of use. From a mobile shopping perspective, however, the impact could differ substantially.

Although many researchers found that men are more inclined to shop online in general, the exception was with online grocery shopping, which saw more female than male shoppers (Reinartz, Dellaert, Krafft, Kumar & Varadarajan, 2011: 53; Shea & Zivic, 2011: 23; Deon, 2011:

5424). Faqih and Jaradat (2015: 40) state that gender is an important indicator showing that women and men have different motivations towards online shopping. Traditionally, the women in a household lead all the major purchase decisions for their families and have deep-rooted preferences as to what and where to buy (Saleem, Khan, Ahmed, Shah & Surti, 2018: 8). For these women, it is generally a planned purchase, which occurs monthly, mostly at a larger supermarket. This is in line with Choi (2013: 16), who found that women are more likely to shop online for groceries, due to women typically being the main shopper of the household. Furthermore, in a study investigating consumers' willingness to use mobile grocery apps, Martínez and Porter (2012: 234) found that women were more willing to buy groceries via mobile apps. Budhiraja and Mittal (2016: 53) corroborate these findings as their results depicted that working women are more inclined to adopt online grocery shopping. Punjnai (2017: 158) supports this view, stating that because of the hectic schedules of working mothers, females prefer online grocery shopping more than men due to its convenience, time-saving aspect and ease of ordering. In their study examining how utilitarian and hedonic values drive customer engagement with mobile grocery shopping apps, Kokkonen and Laukkanen (2019: 4738) discovered that women attach more emotional value to mobile grocery apps. From the above discussion, it can be argued that women will be more prone to adopt same-day delivery apps due to their role in the family and their busy lifestyles. It is believed that same-day delivery apps will be more compatible with females, and they will likely depict heightened intentions to continue using same-day delivery apps.

The literature also suggests differences in the adoption of technology between various age groups. As opposed to older generations who are accustomed to buying groceries from brick-and-mortar stores, the younger generation use technology more frequently to save time and seek convenience (Saleem et al., 2018: 2). The grocery shoppers of the new age are better educated and risk-takers, they try new things and opt for easier solutions to problems. In a study modelling the determinants of repeat purchase behaviour of online grocery shoppers, Choi (2013: 16) discovered that most online grocery shoppers are between the ages of 18 and 34 years, indicating that younger consumers are more inclined to purchase groceries online. These findings are similar to those of Punjnai (2017: 158) who highlights that consumers between the ages of 25 and 44 years are more likely to shop online. Snyman (2014: 44) noted that online grocery shoppers in her study were generally younger than the average Internet user. Congruently, Saleem et al. (2018: 9) reveal that young people, generally between the ages of 20 and 29, are more likely to purchase online, while their older counterparts are less prone to purchase groceries online. Unnikrishnan and Figliozzi (2020: 11) concur as they too report that older consumers (≥ 45 years) are less likely to spend money on home delivery compared to younger respondents. Choi (2013: 15) points out

that online grocery customers are generally younger, have a higher education, have more disposable income and loathe in-store shopping.

The aforementioned empirical evidence may imply that the relationship between lifestyle compatibility and behavioural intention will be moderated by generational cohort (age) and gender.

4.2.13.4.3 The moderating effect of generational cohort and gender on the relationship between perceived risk and behavioural intention

In comparison to the offline and e-commerce business environments, m-commerce involves greater uncertainty and risk, as it operates in a virtual and wireless environment (Gao, Waechter & Bai, 2015: 251). Mobile devices are susceptible to several risks, including the exposure, misuse and interception of sensitive, personal and financial information, and the disclosure of location information, which is transferred over wireless communications (Marinković, Đorđević & Kalinić, 2020: 310). According to Pagani and Malacarne (2017: 138), Internet users' concern for privacy and security has received substantial attention as a key factor that regulates users' willingness to disclose their personal information to online companies.

An extensive search of academic databases (such as EBSCOHost, ScienceDirect and ProQuest) yielded no results pertaining to the moderating effect of generational cohort and gender on the relationship between perceived risk and behavioural intention towards same-day delivery apps. Conclusions were therefore drawn from related e-commerce and m-commerce literature.

Researchers have explored the moderating effect of age and gender on perceived risk and behavioural intention, to provide a more detailed outlook on how privacy and security concerns associated with technology influence different groups (e.g. Aboobucker & Bao, 2018: 25; Chawla & Joshi, 2020: 483; Faqih, 2016: 155; Marriott & Williams, 2018: 20; Wang, 2018: 201). There seems to be consensus that the interaction effect between perceived risk on behavioural intention will be more salient for females than men. For instance, Faqih (2016: 155) discovered that women exhibit higher risk levels than men towards their intention to use the Internet for making purchases. Marriott and Williams (2018: 20) agree as their results show that females are strongly influenced by their overall perceived risk towards mobile shopping. Similarly, in their study, Aboobucker and Bao (2018: 25) considered the factors that influence the adoption of Internet banking and found that perceived risk is more relevant to women than to their male counterparts. These findings coincide with those of Ali and Maideen (2019: 385) and Yapp et al. (2018: 117), who discovered

that females have higher perceived risk towards the adoption of crowdsourcing mobile apps and on-demand service apps than males.

It is furthermore inferred that a higher perceived risk reduces the probability of an older person adopting online shopping since the information technology literacy of older people is usually lower than that of younger users (Lian & Yen, 2014: 136). Aboobucker and Boa (2018: 25) as well as Wang (2018: 201) support this view. Aboobucker and Bao (2018: 25) testified that for the older age category in their study, perceived risk as well as security and privacy of information had a significantly higher moderating effect than on the younger age group. Wang (2018: 201) concurs as perceived risk was reported to impact the elderly's intention to use mobile apps, indicating that older users are concerned about the negative factors, such as privacy and economic conditions, of using mobile apps in general.

Based on the above literature discussion, it can be inferred that the relationship between perceived risk and behavioural intention will be moderated by generational cohort (age) and gender.

4.2.13.4.4 The moderating effect of generational cohort and gender on the relationship between perceived self-efficacy and behavioural intention

In terms of computer and Internet self-efficacy, it was found that older people have low self-efficacy in using technology (Tarhini et al., 2014: 168), the reason being that older individuals often perceive themselves to be too old to learn new skills (Turner, Turner & Van de Walle, 2007: 293). Previous research has found that age differences influence the perceived difficulty of learning a new software application (Morris & Venkatesh, 2000: 121). Tarhini et al. (2014: 168) believe younger adults have lower levels of computer anxiety than their older counterparts, and that these lower levels are associated with less reluctance to engage in opportunities to learn new technological skills. Trahini et al.'s study (2014: 177) exploring e-learning acceptance revealed that the moderating effect of age on the relationship between self-efficacy and behavioural intention was stronger for older respondents. These findings suggest that a lack of confidence in using technology may present more barriers to use for older individuals compared to younger individuals (Trahini et al., 2014: 177).

Many studies have also shown that gender differences are a key attribute that indicates the intention to accept new technologies (Okazaki & Mendez, 2013: 1237). Scholars widely acknowledge that males, compared to females, tend to hold higher perceptions of self-efficacy, indicating that women typically display lower self-efficacy, lower computer aptitude and higher

computer anxiety (Faqih, 2016: 148; He & Freeman, 2009: 1; Lu & Rastrick, 2014: 55; Venkatesh & Morris, 2000: 119). Faqih (2016: 148) reiterates that women tend to have low Internet self-efficacy and high anxiety about Internet shopping technology. In their study, He and Freeman (2009: 1) report that females are less confident with computers because of their inexperience, and as a result feel more anxious about using computers compared to males. Lu and Rastrick (2014: 55) concur and argue that because females have more computer anxiety, less self-efficacy and passive perceptions of technologies, they typically have more discomfort and reluctance to be receptive to new technologies.

The above arguments gave rise to the hypothesis that the relationship between perceived self-efficacy and behavioural intention will be moderated by generational cohort (age) and gender.

4.2.13.4.5 The moderating effect of generational cohort and gender on the relationship between attitude towards use and behavioural intention

Gender differences in the attitude towards technology use have long been explored in scholarly research (Cai, Fan & Du, 2017: 1). Cai et al. (2017: 1) report that studies in the recent two decades continue to provide mixed and contradictory findings about gender differences in attitudes towards technology. On the one hand, researchers have reported that males have more positive attitudes towards technology than their female counterparts (e.g. Chou, Wu & Chen, 2011: 945; Hasan, 2010: 600). On the other hand, the opposite is confirmed – males exhibit more negative attitudes towards technology use than females (e.g. Imhof, Vollmeyer & Beierlein, 2007: 2823). In more recent studies on consumers' attitudes towards new technology, the majority of the findings reveal that males have more favourable attitudes towards new technologies than their female counterparts (e.g. Altawallbeh et al., 2015: 47; Cai et al. 2017: 1; Kotzé, Anderson & Summerfield, 2016: 23; Menya, Banadda & Kiggundu, 2020: 4). Women generally report less confidence in their technical expertise and more negative attitudes towards technology than men (Paul & Thompson, 2018: 1).

Significant differences between age groups towards their attitude toward new technologies have also been widely reported in the literature. Kopaničová and Klepochová (2016: 73) found noteworthy differences between age groups and their attitude toward new technologies in the purchasing process. Similarly, Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva (2014: 464) found that the age of the user introduces significant differences into the proposed relationship between attitude and the adoption of new mobile payment systems. In examining the moderating effects of demographic variables on the attitude towards online shopping, Ansari and Farooqi

(2017: 52) state that age acts as a moderator. The younger the respondent, the more informed, more open, less fearful and more innovative they tend to be (Kopaničová & Klepochová, 2016: 73). It could therefore be inferred that the same attitudinal differences towards same-day delivery apps would be found in the research study.

From the above discussions, it is evident that research pertaining to the moderating effect of generational cohort and gender on the relationship between the independent constructs and consumers' behavioural intention to continue using same-day delivery apps was scarce. Previous research has suggested that age and gender are critical demographic variables that moderate the relationship between consumers' perceptions of technology and their behavioural intentions (Palau-Saumell et al., 2019: 9; Tarhini et al., 2014: 168). Therefore, including the moderating effects of generational cohort and gender differences would improve the predictive and explanatory power of the conceptual model. It will furthermore contribute to the body of knowledge on behavioural intention research in South Africa and offer practical implications for the retailing industry and recommendations for future research.

The theoretically grounded conceptual model presented in Figure 4.1 and discussed below is proposed based on the comprehensive and extensive literature discussion and hypotheses provided in this chapter. To achieve the empirical research objectives developed for the research study, the conceptual model and hypotheses were empirically tested. The interrelationships between the various independent constructs, as presented in this chapter, and behavioural intention were examined to determine their significance in a South African context. The moderating effects of generational cohort and gender on the relationship between these constructs and behavioural intention to continue using same-day delivery apps were also investigated. The theoretical integration of the proposed conceptual model for South African consumers' behavioural intention to continue using same-day delivery apps is discussed next.

4.3 THEORETICAL INTEGRATION

The theoretically grounded conceptual model is developed based on the comprehensive literature discussion as well as the theoretical and empirical evidence of previous research. The extensive literature discussion in this chapter outlined key constructs that potentially influence consumers' behavioural intention to use new technology. Theoretical justification and prior research findings supported the formulation of the hypotheses, intended to provide empirical support to achieve the research objectives of the research study (refer to Chapter 1, section 1.5).

An attempt is made through the theoretical integration discussed in this chapter to investigate whether a theoretical relationship exists between the 11 identified independent constructs and how this relationship can be explained in terms of a theoretically integrated behavioural intention model. It is evident from the extant literature discussion in this chapter that a theoretical relationship does exist between the 11 identified independent constructs and behavioural intention.

The research study espouses the main effects of the UTAUT2 Model as the foundational theory in measuring South African consumers' behavioural intention to continue using same-day delivery apps. The seven constructs from the UTAUT2 Model are included in the conceptual model: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value. The research study furthermore builds on the UTAUT2 Model by incorporating four exogenous mechanisms to determine their significance on South African consumers' behavioural intention to continue using same-day delivery apps. The additional constructs identified from a comprehensive literature search are lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. The theoretical justification was presented, warranting the inclusion of these constructs in the context of the research study. thereby extending the UTAUT2 Model with four additional constructs or exogenous mechanisms. It was furthermore projected that generational cohort (age) and gender impact the relationship between the independent and dependent constructs, as discussed in section 4.2.13 above.

Figure 4.1 graphically depicts the conceptual model presented for the research study. The blue boxes represent the main effects of the UTAUT2 Model that underpin the research study, and the green boxes represent the extension of the UTAUT2 by incorporating four theoretically validated exogenous mechanisms. The conceptual model depicts the moderators and their theorised relationships with grey boxes and arrows.

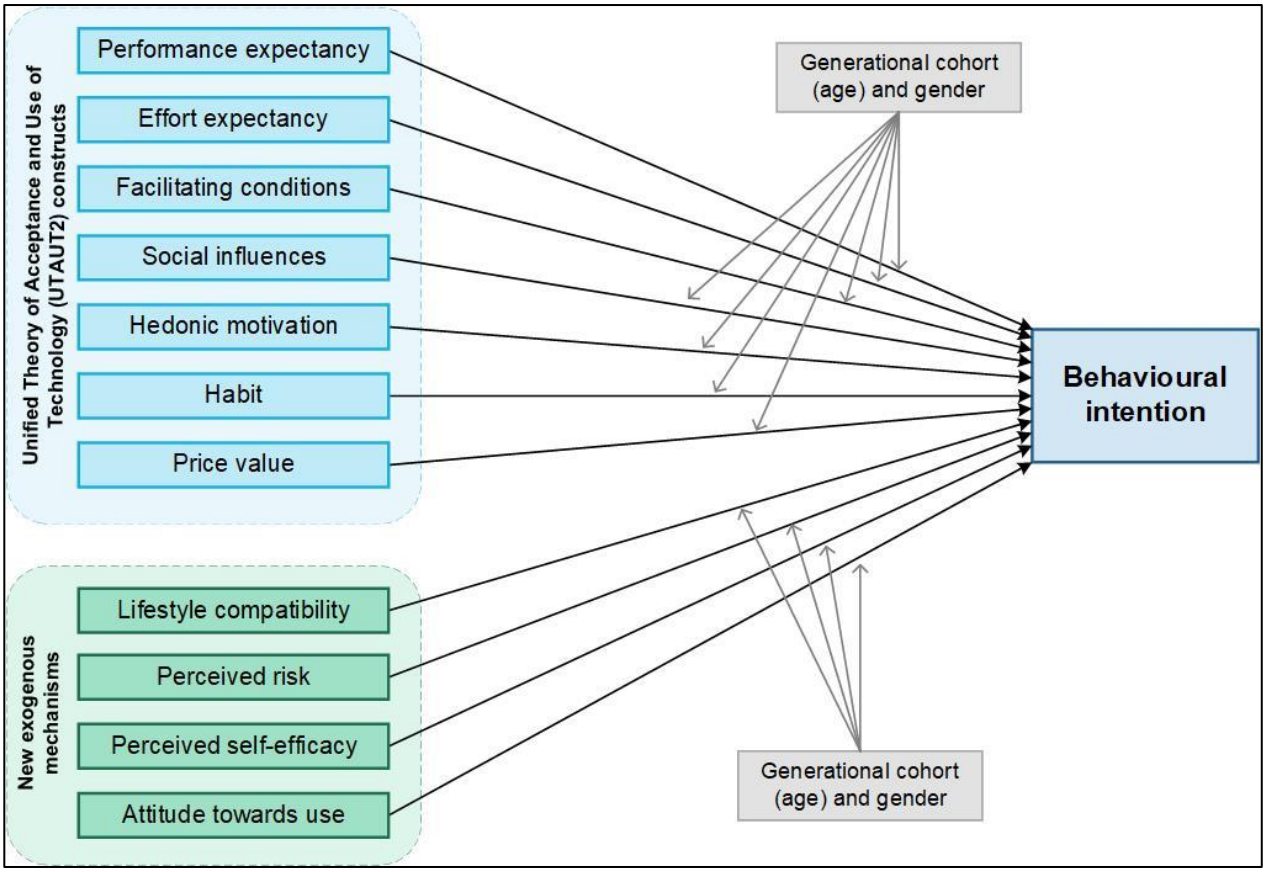

Figure 4.1: Conceptual model and the theoretical interrelationship between constructs

Source: Author's own compilation

Performance expectancy was found to be one of the most important variables of behavioural intention in past research and has received exponential attention from scholars from various research streams (e.g. Chopdar & Sivakumar, 2019: 46; Hamzat & Mabawonku, 2018: 3; Sair & Danish, 2018: 501). Performance expectancy was found to have a significant and positive influence on consumers' acceptance of mobile shopping apps (Soni et al., 2019: 369; Tak & Panwar, 2017: 13), mobile health apps (Nunes et al., 2019: 5; Okumus & Bilgihan, 2014: 31; Yuan et al., 2015: 735), location-based apps (Palos-Sanchez et al., 2017: 12; Roback & Wakefield, 2013: 24), mobile apps in general (Fadzil, 2017: 1; Hew et al., 2015: 1) and m-commerce specifically (Baptista & Oliveira, 2015: 418; Chopdar & Sivakumar, 2019: 46). The literature furthermore confirms the significance of performance expectancy on individuals' intention to adopt on-demand or online food delivery apps (e.g. Erwanti et al., 2018: 13; Flores & Castaño, 2020: 25; Karulkar et al., 2019: 146; Lee et al., 2019: 1; Mensah, 2019: 23; Rasli et al., 2020:679). Musakwa (2021: 48) also established performance expectancy as a factor that influences users' intention to use mobile delivery apps in a study conducted in South Africa. That study investigated, qualitatively, customers' experiences using a specific South African mobile delivery service app (Checkers Sixty60). It is believed that using same-day delivery apps would provide individuals with

the benefits of performing specific activities in everyday situations. It is therefore proposed that the same significant relationship between performance expectancy and consumers' behavioural intention to continue using same-day delivery apps will be found (Hypothesis 1; refer to section 4.2.2 above).

A noticeable relationship between **effort expectancy** and behavioural intention was found in the literature (e.g. Alalwan et al., 2017: 99; Dwivedi, Rana, Chen & Williams, 2011: 166; Hew et al., 2015: 1269; Karulkar et al., 2019: 156). A significant influence on the intention to use smartphones for m-commerce, various types of mobile apps, shopping apps, or delivery apps were reported (e.g. Chopdar et al., 2018: 25; Shaw & Sergueeva, 2016: 14; Soni et al., 2019: 369; Tak & Panwar, 2017: 12; Tan et al., 2017: 570). Previous research furthermore confirms the significance of effort expectancy in the adoption of on-demand service apps and food delivery services or apps (Karulkar et al., 2019: 146; Mensah, 2019: 23; Muangmee et al., 2021: 1306; Musakwa, 2021: iii; Rasli et al., 2020: 679). It is argued that mobile apps, such as same-day delivery apps, are designed to be easy to use and are generally easily learnt. Therefore, a significant relationship between effort expectancy and consumers' behavioural intention to adopt same-day delivery apps is proposed (Hypothesis 2; refer to section 4.2.3 above).

Theoretical and empirical evidence provided substance that **facilitating conditions** influence consumers' behavioural intention. The significant and direct path of facilitating conditions was found to influence the adoption and acceptance of m-commerce (Miltgen, Popovič & Oliveira, 2013: 109; Yu, 2012: 115), mobile wallets (Madan & Yadav, 2016: 237), mobile apps in general (Hew et al., 2015: 1269; Tan et al., 2017: 571), shopping apps (Chopdar et al., 2018: 120; Miladinovic & Xiang, 2016: 50; Soni et al., 2019: 369; Verkijika, 2018: 1672), location-based apps (Zhou, 2012: 135) and tourism-related apps (Escobar-Rodriguez & Carvajal-Trujillo, 2014: 70; Gupta & Dogra, 2017: 156), to name but a few. The literature pertaining specifically to the influence of facilitating conditions on the adoption of same-day delivery apps was limited; however, research related to on-demand delivery apps or food delivery service apps supported the relationship (e.g. Erwanti et al., 2018: 9; Karulkar et al., 2019: 159; Musakwa, 2021: iii). The literature suggests that if users of mobile apps have the necessary knowledge, facilities, resources and support available, they will have heightened intentions to use the specific mobile app (Hew et al., 2015: 1284; Zhou, 2012: 140). It was therefore postulated in this current research study that facilitating conditions will have a significant influence on consumers' behavioural intention to continue using same-day delivery apps (Hypothesis 3; refer to section 4.2.4 above).

Social influence as a direct determinant of behavioural intention was found to be vital in the adoption of shopping apps (Chopdar & Sivakumar, 2019: 42; Miladinovic & Xiang, 2016: 22; Tak & Panwar, 2017: 12), location-based service apps (McKenna et al., 2014: 12), mobile payment initiatives (Khalilzadeh, Ozturk & Bilgihan, 2017: 470), tourism apps (Gupta et al., 2018: 147; Tan et al., 2017: 560), health apps (Okumus, Ali, Bilgihan & Ozturk, 2018: 72), as well as m-commerce and e-commerce apps (Alwahaishi & Snášel, 2013: 68; Chong et al., 2012: 34; Leong et al., 2013a: 5617; Lian & Yen 2014: 133; Madan & Yadav, 2016: 237; Verkijika, 2018: 1672). Empirical evidence furthermore supports the notion that social influence has a significant impact on the adoption of food delivery apps (Lee et al., 2019: 9; Muangmee et al., 2021: 1297; Zhao & Bacao, 2020: 10), on-demand delivery apps (Elango et al., 2019: 1) and online food delivery services (Karulkar et al., 2019: 158; Yapp et al., 2018: 105). Although some studies claim that social influence is insignificant, in emerging economies like South Africa, where the Internet and related technologies are being adopted more slowly than typical, social influences will progressively increase an individual's degree of trust in new mobile apps as others around them do. Individuals in emerging countries have a lot of power to persuade one another to accept, adopt, or employ new technologies (Van Niekerk, 2020: 140). It is believed that when people close to an individual begin using same-day delivery apps, they are more likely to adopt the service as well. The literature discussion affirms the significance of social influence on behavioural intention and therefore the same significant correlation between social influence and behavioural intention to continue using same-day delivery apps is assumed in the research study (Hypothesis 4; refer to section 4.2.5 above).

Hedonic motivation has been researched extensively in the m-commerce domain and has been widely reported to play a vital role in determining technology acceptance behaviours in information systems research. Hedonic motivation was theorised and found to significantly influence consumers' behavioural intention to accept mobile shopping apps (Miladinovic & Xiang, 2016: 50; Tak & Panwar, 2017: 252), m-commerce apps (Lian & Yen 2014: 133; Verkijika, 2018: 1672) and health apps (Okumus et al., 2018: 72), among others. There was a lack of evidence demonstrating a significant relationship between hedonic motivation and behavioural intention to use on-demand mobile service apps, such as food delivery apps and same-day delivery apps. In this context, however, Flores and Castaño (2020: 37), Rasli et al. (2020: 685) and Yeo et al. (2017: 157) report a positive relationship between hedonic motivation and behavioural intention. In a South African study, Musakwa (2021: 60) also reports a significant relationship regarding behavioural intention to use a specific same-day delivery app. It was argued that the number of individuals that are turning to food delivery services has increased due to the current pace of life and the many benefits offered by on-demand service delivery apps (Rasli et al., 2020: 683). In addition, it is suggested

that the more consumers find mobile apps gratifying, the more likely they are to use them (Miladinovic & Xiang, 2016: 50; Rasli et al., 2020: 683). The same significant relationship between hedonic motivation and behavioural intention is therefore inferred for the research study (Hypothesis 5; refer to section 4.2.6 above).

Habit has been recognised in the literature as a key determinant of behavioural intention towards new technology. Empirical results provide evidence that habit positively and significantly influences users' behavioural intention to adopt mobile apps (e.g. Kit et al., 2014: xvi; Moorthy et al., 2019: 1; Tak & Panwar, 2017: 248), mobile shopping apps (e.g. Chopdar & Sivakumar, 2020: 29; Phang et al., 2018: 30; Van Niekerk, 2020: 269), tourism apps (Gupta et al., 2018: 145) and mobile messaging apps (Mutlu & Der, 2017: 175-176). It was furthermore argued that the intention to use a technological system will become less substantial as the habit becomes stronger (Escobar-Rodríguez & Carvajal-Trujillo, 2014: 83). The literature also confirms a significant relationship between habit and behavioural intention to adopt on-demand or food delivery apps (e.g. Erwanti et al., 2018: 9; Lee et al., 2019: 9; Rasli et al., 2020: 685). Researchers claim that as individuals become accustomed to and content with using food delivery apps, the chances of the action or activity being repeated and becoming an occurrence of habit increase. Such behaviour gradually evolves into habit, where users find that they must use mobile apps in their daily routines. As a result, it is postulated in this research study that using same-day delivery apps will become a behaviour of habit, and therefore that there is a direct and significant relationship between habit and consumers' behavioural intention to continue using same-day delivery apps (Hypothesis 6; refer to section 4.2.7 above).

The last construct taken from the UTAUT2 Model, namely **price value**, has been proven to substantially influence individuals' behavioural intention. It is widely believed that the costs involved in using a particular technology would impact consumers' intention towards the technology. Consumers therefore look for higher perceived benefits in comparison to the monetary sacrifices they make in utilising a specific technology (Gupta et al., 2018: 58). Price value has been widely researched and proven to be a significant predictor of intention to use mobile apps (e.g. Chopdar et al., 2018: 117; Fadzil, 2018: 1; Khurana & Jain, 2019: 757; Tamilmani et al., 2018: 2; Tak & Panwar, 2017: 12; Venkatesh et al., 2012: 161). In the context of food delivery services, research also confirms price value as a considerable determinant of intention to use on-demand mobile apps (Erwanti et al., 2018: 9; Flores & Castaño, 2020: 25), food delivery apps (Rasli et al., 2020: 679) and to order food online (Saad, 2021: 535). Given the fact that various costs are involved in using same-day delivery apps, and because of the high data costs in South Africa, it was reasoned that price value will exhibit the same significant influence in the context of the

research study. The literature discussion provides affirmation that price value has a significant influence on consumers' behavioural intention to continue using same-day delivery apps (Hypothesis 7; refer to section 4.2.8 above).

The literature has furthermore alluded to the importance of various exogenous boundary conditions that could be included in the UTAUT2 Model in an attempt to increase the predictive and explanatory power of behavioural intention. Previous research warranted the inclusion of four additional constructs in the context of same-day delivery apps. The four exogenous constructs are represented in the conceptual model by green boxes (see Figure 4.1).

A metatheoretical analysis of behavioural intention and adoption behaviour theories has emphasised the importance of new technological advancements being compatible with an individual's lifestyle and fitting into their daily routines. From a sociological approach, research has recognised lifestyle as a key determinant of an individual's intention to adopt products, services and brands (Belanche et al., 2020: 1). Moreover, due to the fast-paced lives of individuals in a technologically advanced world, individuals are increasingly pressured to incorporate technology into their daily lives. Empirical findings support the notion that **lifestyle compatibility** significantly influences individuals to adopt online shopping (Boateng et al., 2016: 13; Selvakumar & Raghavan, 2017), mobile apps (Arora & Malik, 2020: 106; Belanche et al., 2020: 1) and Internet or mobile banking services (Boateng et al., 2016: 468; Chawla & Joshi, 2017: 410; Shankar & Kumari, 2016: 14; Yang et al., 2021: 1). Limited research could be found on same-day delivery apps, on-demand service apps or food delivery apps. One such study examined the phenomenon of food delivery services from the mobile app user's perspective and how consumers' lifestyles are changing because of the convenience of these apps (Belanche et al., 2020: 1). Belanche et al.'s study (2020: 13) revealed that mobile app lifestyle compatibility has a positive and significant influence on intention to use food delivery services. The emergence of food delivery services could be attributed to the changing nature of the urban consumer (Chai & Yat, 2019: 63). Home delivery services, such as same-day or on-demand delivery apps, are convenient for online shoppers (Chen et al., 2014: 69), and offer quick and convenient meals during or after a busy workday (Chai & Yat, 2019: 63). Additionally, given the pace of life today and the possibility of finding more restaurants and stores that provide home delivery services, mobile app improvements have made home delivery services even more desirable (Belanche et al., 2020: 1; Chai & Yat, 2019: 63). It is argued that an individual's lifestyle would strongly predict their intention to adopt same-day delivery apps because individuals search for alternatives to make everyday tasks easier and adaptable to their lifestyle. The hypothesis was therefore formulated that there is a significant

relationship between lifestyle compatibility and consumers' behavioural intention to continue using same-day delivery apps (Hypothesis 8; refer to section 4.2.9 above).

From the literature discussion, it was apparent that **perceived risk** has been a common extension of the UTAUT2 Model. Advancements in online and mobile technologies, and the widespread use of smart technology worldwide, have led to the development of innovative and functional mobile operating systems that offer users more convenience and efficiency in their daily lives. However, m-commerce, regardless of its exceptional growth, has been accompanied by an increase in mobile users' trepidation about using mobile apps due to the many risks. Several scholars acknowledge that one of the main factors hindering the adoption of mobile apps or e-commerce is users' concern for privacy and security (e.g. Chopdar et al., 2018: 3; Hubert et al., 2017: 181; Kaushik et al., 2020: 12). As a result, researchers have explored the impact of perceived risk on individuals' intention to adopt a new technological innovation (e.g. Ali & Maideen, 2019; Amaro & Duarte, 2015; Chang et al., 2017; Gupta et al., 2018; Kaushik et al., 2020; Marriott & McLean, 2019). Perceived risk has been explored in the context of m-commerce (Vasileiadis, 2014: 187; Verkijika, 2018: 1673), mobile shopping (Marriott & McLean, 2019: 19), mobile apps (Arora & Malik, 2020: 106), online grocery or food shopping (Alaimo et al., 2020: 1; Chai & Yat, 2019: 62; Pauzi et al., 2017: 1), food delivery services (Belanche et al., 2020: 1) and mobile retail apps specifically (Kaushik et al., 2020: 1). Alaimo et al. (2020: 1), Belanche et al. (2020: 1) as well as Chai and Yat (2019: 62) agree that perceived risk is a strong predictor of behavioural intention in the adoption of online food delivery services or mobile delivery apps. Unlike the driving constructs included in the UTAUT2 Model, the literature suggests that perceived risk represents a detractor in the adoption process (Slade et al., 2015: 864). Since research has attested that perceived risk has a negative effect on intentions, it is postulated that there is a significant and negative relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps (Hypothesis 9; refer to section 4.2.10 above).

Perceived self-efficacy was considered an individual characteristic and the UTAUT Model was criticised for not having included it (Moghavvemi et al., 2013: 247). Moghavvemi et al. (2013: 247) are of the opinion that inexperienced users view new technology as complex, and the self-confidence in their ability to handle it has a significant influence on their acceptance behaviours. Empirical findings confirm that self-efficacy meaningfully affects consumers' intention to adopt mobile apps (Lee & Hsieh, 2009: 1; Wu et al., 2007: 65; Wang & Wang, 2008: 405), fitness mobile apps (Wei et al., 2020: 1), location-based service apps (McKenna et al., 2014: 12), mobile banking services (Jeong & Yoon, 2013: 1; Singh et al., 2018: 121), m-commerce (Luarn & Lin, 2005: 873) and mobile data services (Yang, 2010: 117), to name but a few. There has been limited research

on same-day or on-demand delivery apps. One such related study explored the factors that influence consumers' behavioural intention to use on-demand food delivery apps and found personal self-efficacy to be the second most significant predictor of behavioural intention (Elango et al., 2019: 13). Grounded in theoretical validation, perceived self-efficacy is expected to significantly influence consumers' behavioural intention to use mobile apps. It is argued that the more self-efficacious users view themselves to be, the higher their intention to use a new technology will be (Okumus & Bilgihan, 2014: 39; Marriott et al., 2017: 576). It is inferred that perceived self-efficacy has a significant influence on consumers' behavioural intention to continue using same-day delivery apps, as proposed in the conceptual model (Hypothesis 10; refer to section 4.2.11 above).

Lastly, considered spurious in the development of the UTAUT Model due to its negative influence on the relationship between specific significant cognitions, the '**attitude towards use**' construct was omitted from the UTAUT Model. The literature and empirical evidence, however, suggest otherwise. Moghavvemi et al. (2013: 247) are of the view that the UTAUT Model lacks in its ability to measure individual characteristics towards behavioural intention. Several widely used technology adoption theories have found attitude to be a significant predictor of behavioural intention. Furthermore, as discussed in the literature, attitude towards using technology has been reported to be a salient and direct determinant of behavioural intention to accept m-library apps (Hu & Zhang, 2016: 652), m-learning in higher education (Thomas et al., 2013: 84), online banking services (Yeow et al., 2008: 191) and Internet banking (Yuen et al., 2010: 52). Subsequent empirical evidence, however, contradicts Venkatesh et al.'s inclination (2003: 455) that attitude is spurious. For these reasons, scholars recommend that the effects of attitude towards using a technology be further validated and replicated. Attitude towards using food delivery apps was also measured by Cho et al. (2018: 108), Lee et al. (2017: 1468), Shukla and Sharma (2018: 192) as well as Troise et al. (2021: 675) and was found to significantly influence individuals' intention to use these technologies. It is therefore postulated that a positive attitude towards same-day delivery apps will lead to consumers' intention to continue using same-day delivery apps (Hypothesis 11; refer to section 4.2.12 above).

In Venkatesh et al.'s review (2012: 158) of numerous research studies utilising the UTAUT2 Model, they found that most studies only employed a subset of the constructs, particularly by eliminating the intended moderators. To contribute to the predictive and explanatory power of the UTAUT2 Model, the inclusion of two demographic moderators: **generational cohort and gender,** is proposed in this current study. Theoretical validation provides grounds for the moderating effects between the 11 independent constructs and consumers' behavioural intention. Significant

differences between age groups and gender have been widely reported in the literature (refer to section 4.2.13). It is therefore postulated that gender and generational cohort would modulate the influence of the 11 independent constructs on behavioural intention (Hypothesis $12_{(a-k)}$; refer to section 4.2.13 above).

Table 4.4 provides a summary of the hypotheses that have been supported in the preceding sections.

Table 4.4: Summary of hypotheses and proposed moderating effects

	Hypotheses	**Proposed moderating effects**
PE	*H1:* There is a significant relationship between performance expectancy and consumers' behavioural intention to continue using same-day delivery apps.	$H12_a$*:* The relationship between performance expectancy and behavioural intention will be moderated by generational cohort and gender.
EE	*H2:* There is a significant relationship between effort expectancy and consumers' behavioural intention to continue using same-day delivery apps.	$H12_b$*:* The relationship between effort expectancy and behavioural intention will be moderated by generational cohort and gender.
FC	*H3:* There is a significant relationship between facilitating conditions and consumers' behavioural intention to continue using same-day delivery apps.	$H12_c$*:* The relationship between facilitating conditions and behavioural intention will be moderated by generational cohort and gender.
SI	*H4:* There is a significant relationship between social influence and consumers' behavioural intention to continue using same-day delivery apps.	$H12_d$*:* The relationship between social influence and behavioural intention will be moderated by generational cohort and gender.
HM	*H5:* There is a significant relationship between hedonic motivations and consumers' behavioural intention to continue using same-day delivery apps.	$H12_e$*:* The relationship between hedonic motivation and behavioural intention will be moderated by generational cohort and gender.
HA	*H6:* There is a significant relationship between habit and consumers' behavioural intention to continue using same-day delivery apps.	$H12_f$*:* The relationship between habit and behavioural intention will be moderated by generational cohort and gender.
PV	*H7:* There is a significant relationship between price value and consumers' behavioural intention to continue using same-day delivery apps.	$H12_g$*:* The relationship between price value and behavioural intention will be moderated by generational cohort and gender.
LSC	*H8:* There is a significant relationship between lifestyle compatibility and consumers' behavioural intention to continue using same-day delivery apps.	$H12_h$*:* The relationship between lifestyle compatibility and behavioural intention will be moderated by generational cohort and gender.

	Hypotheses	Proposed moderating effects
PR	*H9:* There is a significant and negative relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps.	$H12_i$: The relationship between perceived risk and behavioural intention will be moderated by generational cohort and gender.
PSE	*H10:* There is a significant relationship between perceived self-efficacy and consumers' behavioural intention to continue using same-day delivery apps.	$H12_j$: The relationship between perceived self-efficacy and behavioural intention will be moderated by generational cohort and gender.
ATT	*H11:* There is a significant relationship between a positive attitude towards same-day delivery apps and consumers' behavioural intention to continue using same-day delivery apps.	$H12_k$: The relationship between consumers' attitude towards using same-day delivery apps and behavioural intention will be moderated by generational cohort and gender.

Key: Performance expectancy (PE); Effort expectancy (EE); Facilitating conditions (FC); Social influence (SI); Hedonic motivation (HM); Habit (HT); Price value (PV); Lifestyle compatibility (LSC); Perceived risk (PR); Perceived self-efficacy (PSE); Attitude towards using (ATT)

Source: Author's own compilation

The interrelationships of the theoretically validated hypotheses, as discussed in this chapter, are graphically depicted in Figure 4.1, which served as the foundation for the empirical analyses in an attempt to achieve the primary objective of the research study: to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model.

4.4 CONCLUSION

Chapter 4 offered a metatheoretical analysis of the salient factors that could potentially influence consumers' behavioural intention to continue using same-day delivery apps in a South African context. A theoretically grounded conceptual model for customers' behaviour intention to continue using same-day delivery apps in a South African environment was presented. The proposed conceptual model was developed based on the comprehensive literature discussion and theoretical and empirical evidence found in several scholarly works. Eleven theoretically derived constructs influencing consumers' behavioural intention to adopt new technology were identified and proposed in the conceptual model (see Figure 4.1): performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. The theoretical differences between subgroups were furthermore identified and therefore it was postulated that generational cohort and gender will moderate the relationship between the independent and dependent constructs. The proposed dimensions identified in the literature not only add to the

predictive and exploratory power of the UTAUT2 Model by utilising the model in a different context and with different outcome mechanisms, but also extend the model by incorporating additional exogenous mechanisms that potentially influence consumers' behavioural intention.

The following literature research objectives were achieved in this chapter:

Research objective 3: To identify, in the literature, theoretically and empirically validated constructs that significantly influence consumers' behavioural intention towards new technology.

Research objective 4: To conceptualise the identified constructs and investigate the theoretical interrelationships between the independent constructs and behavioural intention, relevant to the context of the research study.

Research objective 5: To identify and conceptualise the moderating constructs (generational cohort and gender) and investigate their effect on the independent constructs and behavioural intention.

Research objective 6: To develop a conceptual model based on the theoretical relationship dynamics between the independent constructs, the moderating effects and behavioural intention.

The literature research objectives developed for the research study have therefore been achieved in Chapters 2, 3 and 4.

Chapter 5 focuses on the empirical research pertaining to the research study.

CHAPTER 5:
RESEARCH METHODOLOGY

5.1 INTRODUCTION

Chapter 5 focuses on outlining the central concepts of the research undertaken to conduct the empirical investigation. The chapter commences with an overview of the research process, investigating each step to offer in-depth insights into the methodological methods, techniques and choices that underpin the research study. The research question and objectives are revisited, followed by a review of the literature and the development of a conceptual model, as discussed in Chapters 3 and 4, respectively. Subsequently, the research design which follows the structure of the 'research onion', conceptualised by Saunders et al. (2019: 174), will be discussed and applied. The selected philosophy and approach to theory development will be discussed, followed by an outline of the methodological choice, research strategy, time horizon and the data collection techniques and procedures. Thereafter, the population and sample for the study are discussed, providing insights into the sampling techniques and methods employed. The research instrument process is then discussed, outlining the constructs, scale design and structure, sample items and scales, and the pre-testing process that was followed. Finally, the data analysis procedure and techniques utilised in the study will be discussed. The chapter concludes with a description of the procedure that was followed to adhere to ethical responsibility requirements.

5.2 THE RESEARCH PROCESS

Research is a process that is undertaken systematically with a clear purpose, to find things out (Saunders et al., 2019: 5). In the social sciences sphere, research entails the systematic study of society, the patterns in it and the processes that shape what people do (Walter, 2019: 4). Research aids in the attainment of objective conclusions about the real world by employing scientific methods about knowledge and empirical evidence (Babin, D'Alessandro, Winzar, Lowe & Zikmund, 2020: 4). Social research therefore involves investigating and seeking answers to the questions raised about our social world (Walter, 2019: 4).

The scientific method employed in the research study is outlined in Figure 5.1 below. The research process provides an orderly and planned overview of the general sequence of activities and approaches undertaken in the research study (Brown et al., 2018: 15; Hefer, 2017: 117). The research process, as adapted and collated from Bryman et al. (2014: 32), Kumar (2019: 43) and

Saunders et al. (2019: 12; 174) describe the systematic and logical plan to achieve the research objective for the study. Figure 5.1 illustrates the steps in the research process. Each step in the process will be discussed in detail in relation to the research study in the following sections.

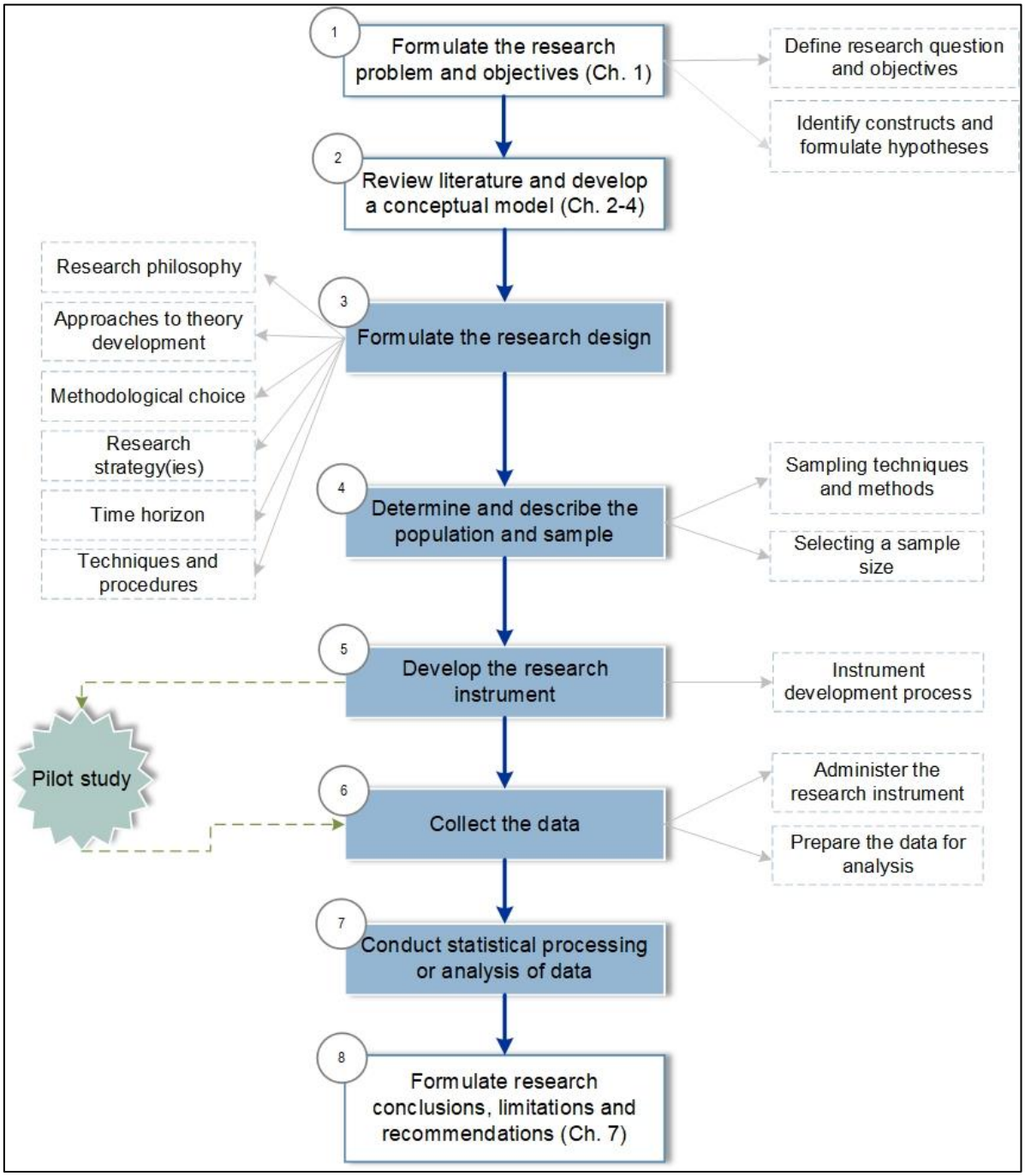

Figure 5.1: Research methodology process

Source: Adapted from Bryman et al. (2014: 32); Kumar (2019: 43); Saunders et al. (2019: 12; 174)

5.2.1 STEP 1: RESEARCH PROBLEM AND OBJECTIVES

The first step in the research process, as shown in Figure 5.1, is to determine the research problem and formulate research objectives. A research problem refers to any question, dilemma, or opportunity that becomes the basis of investigation and requires a response in the form of a structured scientific inquiry (Frankfort-Nachmias, Nachmias & DeWaard, 2015: 46; Kumar, 2019: 485; Malhotra, 2019: 33).

The research problem, explored in Chapter 1, section 1.4, stems from the limited literature on consumers' behavioural intention to continue using same-day delivery apps within a South African context. Despite the widespread use of mobile shopping apps globally, little research focuses on same-day delivery apps in the South African retailing industry.

To address this gap, the research aims to provide insights into South African consumers' behavioural intention towards the continued used of same-day delivery apps, extending the UTAUT2 Model. This research study intends to fill the literature gap, offering a validated behavioural intention model for South African consumers using same-day delivery apps.

The research problem guided the development of a research question and a primary research objective that served to provide direction to the research process. A research question states the major aim of the research in a refined statement, specifying the key idea that the researcher seeks to investigate and identifies specific components of the research problem (Malhotra, 2019: 385; Walter, 2019: 13). The research question, from which the specific research objectives were derived, was:

Research question: What factors influence South African consumers' behavioural intention to continue using same-day delivery apps?

Derived research objectives were formulated in terms of the literature review and empirical study. A research objective or aim is a broad statement of goals summarising the general intention or desired outcomes to be achieved at the end of the research journey (Kumar, 2019: 485; Saunders et al., 2019: 815; Walter, 2019: 33).

The **primary research objective** was to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model.

In terms of the literature review, the specific secondary research objectives were formulated as follows:

Research objective 1: To discuss mobile apps and same-day delivery app usage from an international and South African context and in relation to the retailing industry.

Research objective 2: To assess the scientific and methodological rigour of the UTAUT2 Model to position an improved theoretical paradigm to use the model as the foundational framework for the research study.

Research objective 3: To identify, in the literature, theoretically and empirically validated constructs that significantly influence consumers' behavioural intention towards new technology.

Research objective 4: To conceptualise the identified constructs and investigate the theoretical interrelationships between the independent constructs and behavioural intention, relevant to the context of the research study.

Research objective 5: To identify and conceptualise the moderating constructs (generational cohort and gender) and investigate their effect on the independent constructs and behavioural intention.

Research objective 6: To develop a conceptual model based on the theoretical relationship dynamics between the independent constructs, the moderating effects and behavioural intention.

In terms of the empirical study, the specific secondary research objectives were formulated as follows:

Research objective 1: To explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market.

Research objective 2: To explore the suitability of the individual items measuring the latent constructs in the research instrument involving a sample of South African consumers.

Research objective 3: To assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention.

Research objective 4: To examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers.

Research objective 5: To evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model.

Research objective 6: To empirically assess the interaction effects between the independent variables and the dependent variable, and two demographic conditions (moderators), namely generational cohort and gender.

Research objective 7: To assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps.

Research objective 8: To formulate conclusions and make recommendations for the marketing and retailing industry, and for possible future research, based on the results of the research study.

From the systematic integration of previous research discussed in Chapter 4, various independent constructs were identified as factors that could potentially influence consumers' behavioural intention to continue using new technology. The literature review led to the development of theoretically motivated hypotheses theorising the interrelationships between the identified constructs and behavioural intention.

Step 2 of the research process, as shown in Figure 5.1, involves conducting a thorough review of existing literature to develop a theoretically grounded and integrated conceptual model. Step 2 was discussed in depth in Chapters 2, 3 and 4, and will be summarised in the next section.

5.2.2 STEP 2: REVIEW LITERATURE AND DEVELOP A THEORETICALLY INTEGRATED CONCEPTUAL MODEL

The second step in the research process, illustrated in Figure 5.1, focuses on reviewing existing literature and constructing a conceptual model from secondary data. Secondary research involves analysing historical data gathered for a specific research opportunity or problem (Marcouse, 2017: 16). Chapters 2, 3 and 4 of the study detail the literature relevant to the research, the evaluation of existing literature and the development of the conceptual model. Integration of existing literature and the development of the conceptual model were addressed in Chapter 4.

Secondary research aimed to achieve the following objectives:

- To explore mobile apps and same-day delivery apps' usage in both international and South African retail contexts (Chapter 2);
- To assess the scientific and methodological rigour of the foundational theory used in the construction of the conceptual model – the UTAUT2 Model (Chapter 3);
- To explore scholarly works to identify and conceptualise exogenous constructs influencing consumers' behavioural intention towards new technology, specifically same-day delivery apps (Chapter 4).

To identify factors that theoretically influence consumers' behavioural intention to continue using same-day delivery apps in a South African retailing context, a thorough literature review was conducted as an evaluative report on behavioural intention. This was reported on in Chapter 4 of the research study, where justification for the inclusion of the various independent constructs was described, assessed, summarised and discussed in relation to the context of the research study. The literature review acted as the theoretical base for the research study and assisted the researcher in determining the nature of the study.

Theory regarding behavioural intention was read, evaluated and analysed to form relationships to identify and articulate the various factors that hypothetically influence consumers' behavioural intention. The purpose of conducting a thorough literature analysis of behavioural intention was to determine the significance of various exogenous mechanisms and their influence on consumers' behavioural intention specifically towards mobile apps and same-day delivery apps. The underlying behavioural intention construct in the existing theory was used as the foundation for the development of the conceptual model and as the groundwork for the empirical study. The literature review was guided by the primary research objective to examine the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development of a conceptual model.

A literature review was conducted, incorporating numerous sources of theory, including academic journals, textbooks, academic studies and the web, among others. Deductive reasoning was adopted to derive conclusions about specific instances based on a known general premise (Venter & Van Zyl, 2017: 8). The researcher used deductive reasoning to examine several latent exogenous mechanisms that were found to significantly affect consumers' behavioural intention to use different technological systems and/or devices in a variety of earlier academic research. The significance of these constructs was further investigated in the context of mobile app adoption behaviour, same-day delivery apps specifically and within a retailing context. These constructs

were incorporated into the conceptual model's development based on previous empirical findings and the importance of exogenous mechanisms in the context of mobile app adoption research.

An attempt was made through the theoretical integration discussed in Chapter 4 to investigate whether there is a theoretical relationship between the 11 independent constructs (performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use) and how these relationships can be explained using a theoretically grounded behavioural intention model. It is evident from the extant literature discussed in Chapter 4 that a theoretical relationship does exist between the 11 identified constructs and behavioural intention.

In the research study the main effects of the UTAUT2 Model were espoused as the foundational theory in measuring consumers' behavioural intention to continue using same-day delivery apps. The seven constructs from the UTAUT2 Model were included in the conceptual model: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value. The research study furthermore built on the UTAUT2 Model by incorporating four additional exogenous mechanisms to determine their significance on consumers' behavioural intention to continue using same-day delivery apps in a South African context. The additional constructs identified from a comprehensive literature search are lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. The theoretically derived conceptual model is presented in Chapter 1 (Figure 1.3) and Chapter 4 (Figure 4.1).

When secondary research yielded no solution to the main research problem identified, it was necessary to gather primary data. To confirm the constructs of the proposed conceptual model identified, and empirical study was required. Primary research involves research that is conducted by gathering empirical evidence. To conduct an empirical study, a research design needed to be determined, the next step in the research process.

5.2.3 STEP 3: RESEARCH DESIGN

The third step of the research process, as illustrated in Figure 5.1, is to formulate the research design that will be used. A research design, or strategy of inquiry, provides a framework and structure to the research study that guides the collection and analysis of the subsequent data (Bryman et al., 2014: 100), in order to address the research question(s) and/or realise the research objectives (Saunders et al., 2019: 173). The 'research onion' framework proposed by Saunders et al. (2018: 174) will be used to outline how the research will be structured. The 'research onion'

has several layers, each which examines the researcher's decisions and choices. From the outermost layer, the six layers of the 'research onion' include the research philosophy, approaches to theory development, methodological choices, research strategy, time horizons and techniques and procedures.

To select the most suitable research design, it is essential to first consider the purpose of the research. Research can be designed to achieve one of four purposes, or a combination of these, namely exploratory, explanatory and descriptive purposes (Saunders et al., 2019: 186). Exploratory research helps the researcher understand consumer attitudes or behaviours by asking open-ended questions about a specific topic (Venter & Van Zyl, 2017: 7). Descriptive research uses quantitative data to answer specific research questions and provide a more accurate picture of a situation, event, or group of people (Saunders et al., 2019: 187). Causal research, on the other hand, allows the researcher to establish cause-and-effect relationships between variables by collecting data (Hair et al., 2020: 162).

The purpose of this study's research design was classified as exploratory and descriptive. The purpose of exploratory research is to gradually narrow the scope of the research topic and transform ambiguous problems into well-defined ones that incorporate specific research objectives (Zikmund et al., 2017: 22). Exploratory research is utilised when the research question is vague, or little theory exists, to develop theoretical frameworks and hypotheses (Hair et al., 2020: 162; Venter & Van Zyl, 2017: 87). Exploratory research serves three main purposes: to gratify the researcher's curiosity and desire for understanding a particular topic or phenomenon, to regulate which methods are used in a research project and to explore the probability of conducting more rigorous research (Du Plessis, 2018: 175).

Descriptive studies are designed to describe characteristics, or the relationship between characteristics, of the population under investigation (Brown et al., 2018: 113; Zikmund et al., 2017: 24). The focus of descriptive studies is to describe a situation, phenomenon, person or groups of people, or an environment, in detail (Venter & Van Zyl, 2017: 88). Descriptive research aims to answer questions about 'who', 'what', 'where', 'when' and 'how' related to the phenomenon or object being investigated. A descriptive research methodology is suitable mainly for studies that seek to determine the attitudes or opinions of various groups of individuals (Baumgartner et al., 2021: 16). The purpose is often to generalise findings to a population, and therefore it relies on the representativeness of the sample to the target population and on highly accurate levels of data collection and analysis methods (Venter & Van Zyl, 2017: 89). Descriptive research is often used to uncover the nature of shopping behaviour and consumer behaviour in general (Zikmund et al.,

2017: 24). The research study was descriptive as the constructs under investigation in the extant literature review were discussed and conceptualised, and a conceptual model for determining the factors that influence consumers' behavioural intention to continue using same-day delivery apps was proposed. An empirical study incorporates descriptive statistics, such as the reporting of means, standard deviations, skewness and kurtosis, to describe the characteristics of the collected data.

5.2.3.1 Research paradigm

Determining the research paradigm is vital for devising an appropriate research methodology as research philosophies guide the way in which information is gathered, evaluated and applied (Taylor, 2011). The researcher's paradigm (or philosophy) contains important assumptions about the researcher's view of the relationship between knowledge and the process by which it is developed (Ahmed, Opoku & Aziz, 2016: 81). These paradigms define the views of the research study and depict a researcher's perception of how knowledge can be created and constructed in a rigorous and meaningful way to answer a research problem (UKEssays, 2018).

Philosopher and seminal author Kuhn (1962) first used the word 'paradigm' to explain a philosophical way of thinking (in Perera, 2018: 4). These paradigms, or philosophies, relate to a system of beliefs and assumptions about the nature and development of knowledge (Collins, 2019: 42; Saunders et al., 2019: 130). A research paradigm fundamentally constitutes a researcher's philosophical orientation about abstract beliefs and principles that shape how a researcher sees the world, which has significant implications for decisions made in the research process (Kivunja & Kuyini, 2017: 26). Kuhn (1962) and Guba (1990) state that a research paradigm is a set of common beliefs and agreements shared between scientists about how problems should be understood and addressed (in Perera, 2018: 4). A paradigm is a basic belief system and theoretical framework with assumptions about ontology, epistemology, axiology and methodology (Rehman & Alharthi, 2016: 51; Taylor, 2011):

- *Ontology* is a branch of philosophy that denotes "… the nature of our beliefs and reality" (Saunders et al., 2019: 810). It is concerned with the assumptions researchers make to believe that something makes sense or is real (Kivunja & Kuyini, 2017: 27). Ontology is the theory of existence, one's interest in what exists, and is based on assertions of a paradigm about reality and truth (Žukauskas, Vveinhardt & Andriukaitienė, 2018: 128). Hatch and Cunlife (2006: 370) explain that ontology is related to a researcher's assumptions about whether reality is objective or subjective.

- *Epistemology* refers to the assumptions about knowledge, what constitutes acceptable, valid and legitimate knowledge and how knowledge is communicated to others (Saunders et al., 2019: 133). It is the epistemological question that leads researchers to debate the possibility and desirability of objectivity, subjectivity, causality, validity and generalisability (Rehman & Alharthi, 2016: 52).

- *Axiology* denotes the role of values and ethics that need to be considered when planning a research proposal (Saunders et al., 2019: 134). It is considered the philosophical approach to making decisions of value and involves defining, evaluating and understanding concepts of right and wrong behaviour relating to research (Kivunja & Kuyini, 2017: 28).

- *Methodology* is "… an articulated, theoretically informed, approach to the production of data" and refers to the study and critical analysis of data production techniques (Rehman & Alharthi, 2016: 52). Methodology ultimately guides the researcher in deciding what type of data is required for a study and what data collection methods and techniques are the most appropriate.

Consumer behaviour research, particularly in the field of marketing, has traditionally followed a positivist research paradigm due to the paradigm's logical approach in examining consumer behaviour within various decision-making models (Kallier, 2022: 131; Zeithaml, Verleye, Hatak, Koller & Zauner, 2020: 410). However, recognising the limitations of the positivist research paradigm in comprehensively exploring different facets of consumer behaviour, researchers turn to research paradigms like post-positivism (Maksimović & Evtimov, 2023: 209). The post-positivism paradigm originated from the collapse of the positivist perspective in 1930 and is a dominant paradigm generally applied in social science research (Du Plessis, 2018: 15). Post-positivism acknowledges that the consumer's reality cannot be fully apprehended (Creswell & Creswell, 2018: 7). The current research study acknowledges that consumers may not always be rational, and that consumer behaviour is not something that can be known perfectly. The study's goal is to provide relevant, authentic knowledge about consumer's behavioural intention to continue using same-day delivery apps. As a result, the post-positivist research paradigm, as well as its related statistical data collection and analysis methodologies, is deemed most suitable for unravelling the factors that influence consumer's behavioural intention in the context of South Africa.

Post-positivism is a metatheoretical stance where theories, propositions, hypotheses, background knowledge and values of the researcher can influence what is observed (Robson, 2002: 624).

Post-positivists pursue an objective epistemology in seeking absolute truths and acknowledge researchers' probable prejudices and own world views in the collection and interpretation of data (Court, 2020; Leedy & Ormrod, 2016: 7-8; Vosloo, 2014: 305). Post-positivistic researchers hold a critical realism ontology and postulate that reality can never be fully apprehended, only approximated, and assume that reality has a material existence independent of a researcher's thinking that can be measured and studied (Goodyear-Smith & Mash, 2019). Rather than attempting to explain how something works, post-positivist researchers attempt to comprehend why individuals or things behave in a certain way or reveal power relationships and structures (Du Plessis, 2018: 15). Post-positivistic researchers therefore develop well-formulated hypotheses and well-defined problems and methods and test their theories scientifically to search for meaning in specific cultural and social contexts (Du Plessis, 2018: 15).

The methodology used in the post-positivist paradigm is conducted in a natural setting and the researcher seek to determine the purpose and meaning individuals ascribe to their actions by bringing together theory and practice (Goodyear-Smith & Mash, 2019; Henderson, 2011: 343). These researchers believe in multiple perspectives from respondents as opposed to a single reality (Vosloo, 2014: 305). From a methodological stance, post-positivists are open to different methodological approaches, but they favour quantitative research methods (Vosloo, 2014: 305). Laher, Fynn and Kramer (2019: 305) state that post-positivism suggests that there is a set of truths and causal relationships that exist, which can be measured and analysed quantitatively. Post-positivists value ethics in research and strictly adhere to ethical principles and codes of conduct (Laher et al., 2019: 305).

The post-positivist paradigm also seeks to explore the impact of axiology on the research. Post-positivists acknowledge the inevitability of bias, although undesirable, and emphasise the importance of actively mitigating and rectifying any biases that may arise (Melegati & Wang, 2021:46). To ensure the quality of post-positivist research, criteria such as internal and external validity are examined using statistical confidence levels (Kallier, 2022: 132). Post-positivism employs abstract theories built upon existing knowledge to construct empirical knowledge (Leedy & Ormrod, 2016: 30).

The characteristics of the post-positivistic research paradigm are summarised in terms of the four underlying assumptions related to the ontology, epistemology, axiology and methodology of the paradigm (see Table 5.1).

Table 5.1: Characteristics of post-positivist research paradigm

	Post-positivist paradigm
Ontology (*nature of reality or being*)	• There exists a single absolute reality that is understood and quantified with limitations • The perception of truths is impacted by social, cultural and historical contexts • Critical realism • One reality, comprehensible within a specified level of probability
Epistemology (*what constitutes acceptable knowledge*)	• Modified dualist-objectivist • Objectivity and the autonomy of research subjects are vital • The results are true with a certain level of probability • Objectivity is important; the researcher manipulates and observes in a detached, objective manner
Axiology (*nature of ethical behaviour*)	• Value-free research • The researcher maintains impartiality and emotional detachment from the data • Researcher maintains objectivity throughout the research process • Respect privacy; informed consent; minimise benevolence; justice/equal opportunity
Methodology (*the process and procedures of the research*)	• Critical multiplism • Rigorously structured and regulated • Utilises large sample sizes • Mainly focused on quantitative methods, but may incorporate mixed methods • Interventionist; decontextualised • Research is considered scientific when internal and external validity, reliability and objectivity are appropriately addressed

Source: Adapted from Du Plessis (2018: 16-17); Kallier (2022: 131); Leung and Shek (2018: 2); Mertens (2017)

The purpose of the post-positivistic paradigm is to explore the significance within particular social and cultural settings by searching for concepts, beliefs and ideas that can be applied universally (Du Plessis, 2018: 15). Post-positivists are pragmatists who perceive reality as socially constructed and strive to uncover the meaning of reality as understood by individuals (Du Plessis, 2018: 15). The aim of the research study was to generate precise and unambiguous knowledge regarding the factors that influence consumers' behavioural intention to continue using same-day delivery apps in a South African context. The researcher maintained a post-positivistic approach throughout the research study by remaining objective and an independent observer throughout the research process.

5.2.3.2 Approaches to theory development

The extent to which research is concerned with theory testing or theory building is often portrayed in three contrasting approaches, namely deductive, inductive or abductive (Saunders et al., 2019: 152). A deductive approach is a logical process of formulating conclusions from rigorous scientific and empirical research that is derived from existing theories and literature, the development of hypotheses and the empirical analysis of collected data (Khan & Quadrat-Ullah, 2021: 51; Saunders et al., 2019: 153; Venter & Van Zyl, 2017: 8). Research based on a deductive approach starts with a sound theoretical base and specific hypotheses and can be generalised to members of the observed population once the theory has been tested and the hypotheses either accepted or rejected (Khan & Quadrat-Ullah, 2021: 51; Venter & Van Zyl, 2017: 8). Deductive research is a structured approach that is dependent on laborious scientific rules and methods of sampling and focuses on quantitative research methods (Khan & Quadrat-Ullah, 2021: 51). An inductive approach, on the other hand, draws inferences from observing particular facts or occurrences (Venter & Van Zyl, 2017: 9). An abductive approach is used when data is collected to explore a phenomenon, identify themes and explain patterns, in order to generate new or modify existing theory which is subsequently tested through additional data collection (Saunders et al., 2019: 153).

The research study embraced a deductive approach, which is better suited to a post-positivist paradigm (Venter & Van Zyl, 2017: 8). The deductive approach is furthermore proposed as the research approach moves from theory to an empirical investigation. Hypotheses were deductively formulated from an extensive literature search on consumers' behavioural intention to adopt and continue using new technologies. These hypotheses were empirically tested to examine the outcomes and modify the existing theory accordingly. A deductive approach was furthermore followed as it allows for the possibility to explain causal relationships between concepts and constructs, concepts can be measured quantitatively, and generalisability of the observed population is possible. The research was conducted independently, and an adequate sample size was selected to generalise the results of the study.

5.2.3.3 Methodological choice

The methodological approach is a systematic plan and procedure that encompasses various steps, starting from broad assumptions and extending to detailed methods of data collection, analysis, and interpretation (Chetty, 2016). It is the strategy that is adopted to conduct the research. Three methodological research approaches can be adopted, namely quantitative,

qualitative or a mixed method research approach (Saunders et al., 2019: 174). In this research study, a quantitative research approach was espoused.

Quantitative research is a structured approach that scrutinises relationship variables, which are measured numerically and analysed using a range of statistical, mathematical and graphical techniques (Saunders et al., 2019: 178). Bryman et al. (2014: 31) describe quantitative research as "… a distinctive research approach that entails the collection of numerical data, regards the relationship between theory and research as deductive, prefers a natural science approach in general, and adopts an objectivist conception of social reality". A quantitative research design is generally associated with the positivism and post-positivism research paradigms, especially when used with predetermined and highly structured data collection techniques (Venter & Van Zyl, 2017: 8; Saunders et al., 2019: 176). Unlike qualitative research, quantitative research is based on the premise that the world is stable; it uses statistical analysis on parameter values for conclusions (Bairagi & Munot, 2019: 8). Quantitative research generally provides immediate results of the phenomenon under investigation at one point in time and answers questions such as 'what', 'why', 'who', 'how much' and 'how many' (Ahmed et al., 2016: 82).

The purpose of the research study was to determine the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps. To determine the significance of these factors, structured and statistical data were required to quantify and categorise the key factors identified by respondents. A quantitative research approach would therefore yield statistical inferences of the key factors that lead to behavioural intention to continue using the technology in question. Statistical inferences allowed the researcher to rank the factors according to importance, identify the factor(s) with the most impact on behavioural intention, determine underlying interrelationships between constructs and investigate the interaction effect of the two moderators on the relationship between the independent constructs and behavioural intention. A quantitative research approach was furthermore adopted as it incorporates control measures to ensure the validity of data and the reliability of results (Saunders et al., 2019: 178) to develop a statistically sound behavioural intention model. A highly structured data collection and analysis method was used to test the conceptual model and hypotheses and draw inferential conclusions from the results.

5.2.3.4 Research strategy

A research strategy is a plan that outlines how a researcher would approach answering the research question in order to attain a goal. The research strategy is the methodological link

between the philosophy and subsequent choice of methods to collect and analyse data (Saunders et al., 2019: 189). The research strategies that can be chosen for a specific research study include experiments, surveys, archival and documentary research, case studies, ethnography, action research, grounded theory and narrative inquiry (Saunders et al., 2019: 190). Quantitative research can be classified as either experimental research or survey research (Leung & Shek, 2018: 2; Mertler, 2019). Experimental research involves the principle of manipulating the independent variables and examines the cause-and-effect relationship on the dependent variable by controlling the effects of other variables (Leung & Shek, 2018: 3).

Survey research is widely recognised as one of the most prevalent research designs in the social sciences and is primarily used to obtain a quantitative depiction of attitudes, trends or opinions within a sample (Du Plessis, 2018: 176). Survey research entails the process where a sample of individuals from a selected population is presented with a series of questions in the form of a structured questionnaire (Venter & Van Zyl, 2017: 132). Surveys allow researchers to collect data that can be analysed using descriptive and inferential statistical techniques (Saunders et al., 2019: 193). In addition, survey research allows researchers to suggest possible reasons for particular relationships between variables and to provide conceptual models of these relationships (Saunders et al., 2019: 194).

A survey research strategy is suggested for this study to align with the study's objectives (see Chapter 1 and section 5.2.1 above) as well as the research philosophy and approach outlined above. The selection of survey research was motivated by several factors. Firstly, it aligns with a post-positivist, deductive, and quantitative research approach, making it suitable for exploratory and descriptive research (Saunders et al., 2019: 193). Secondly, survey research permits researchers to make inferences and propose possible explanations for relationships between constructs and produce conceptual models (Saunders et al., 2019: 194). Thirdly, researchers have control over the research process. Fourthly, surveys facilitate the collection of extensive data about constructs, such as the factors influencing consumers' behavioural intentions (Venter & Van Zyl, 2017: 133). In the fifth place, survey research is less costly and less time-consuming and, lastly, findings generated from survey research are statistically representative of the whole population (Saunders et al., 2019: 194).

5.2.3.5 Time horizon

Research studies are generally conducted at a given point in time and represent an exact snapshot in time (cross-sectionally), or they are conducted multiple times over a period of time (longitudinal).

Cross-sectional studies involve the investigation of a particular phenomenon at a single point in time and are accordingly conducted over a short period of time using a sample from the population (Saunders et al., 2019: 212; Venter & Van Zyl, 2017: 8).

A cross-sectional survey design was selected for this research study as it involved data collection at a specific moment in time to determine which factors influence South African consumers' behavioural intention to continue using same-day delivery apps. Cross-sectional studies are furthermore easier managed, cost-effective, generally associated with survey research and often used in exploratory and/or descriptive research studies (Du Plessis, 2018: 177).

The techniques and procedures represent the centre of the 'research onion' and describes what data are collected, the sampling techniques, the data analysis and the material used for the research (Saunders et al., 2019: 174). These techniques and procedures will be discussed in the sections to follow.

5.2.4 STEP 4: POPULATION AND SAMPLE

The fourth step of the research process, as shown in Figure 5.1, is to determine and describe the target population and clarify the sampling strategy.

A population comprises a full set of cases or elements, generally a group of participants from which the researcher seeks knowledge or information (Babbie, 2014: 119; Chadwick, 2018: 2; Saunders et al., 2019: 294) to generalise the results of the study (Salkind, 2018: 85). The target population is "… a complete set of cases or group members that is the actual focus of the research inquiry, and from which a sample may be drawn" (Saunders et al., 2019: 818). Walter (2019: 120) states that it is important to delineate precisely and unambiguously who or what encompasses the population. By contrast, a sample is drawn from the target population and consists of a subset of the population under investigation from which conclusions are drawn (Salkind, 2018: 85). It is important for the sample to be representative of the entire population in order to ensure valid and generalisable findings (Du Plessis, 2018: 177). Saunders et al. (2019: 296) illustrate the conceptualisation of a population, target population and sample graphically (see Figure 5.2):

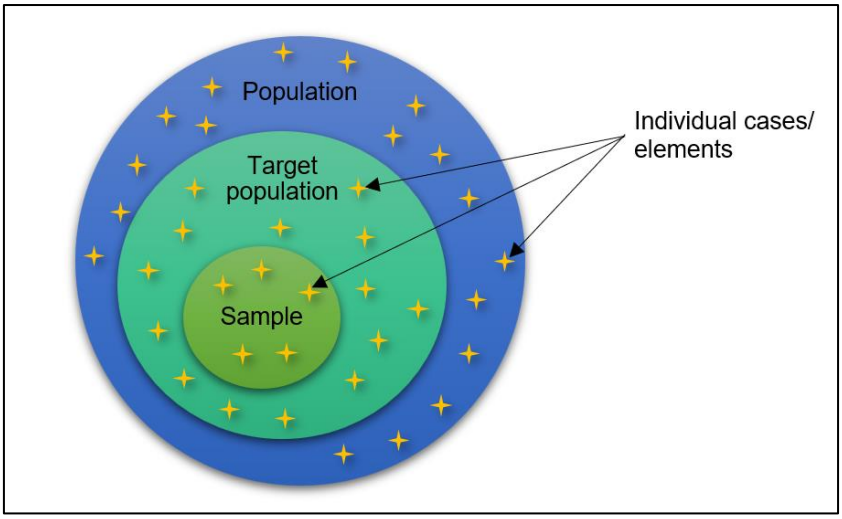

Figure 5.2: Population, target population, sample and individual case
Source: Saunders et al. (2019: 296)

In research, the population refers to the full set of cases or elements from which a sample is taken (Saunders et al., 2019: 294). The population, as identified for the research study, consisted of consumers residing in South Africa. A consumer is any individual who purchases products and/or services for personal use. During the 2021 mid-year population census, the South African population was estimated to have increased to 60.14 million citizens (Statistics South Africa, 2021: vi). The total quarterly consumer spending in South Africa during the third quarter of 2020 amounted to R1.86 trillion, compared to R1.79 trillion prior to the impact of the COVID-19 worldwide pandemic (Statista, 2021d). Due to the increased demand for home deliveries brought about by the COVID-19 pandemic, online retailing in South Africa more than doubled in 2020/2021, with a total of R30.2 billion in online retail spending (World Wide Worx, 2021b). Moreover, it is estimated that 24.5 million South Africans use smartphone devices, which accounts for more than a third of the country's population (O'Dea, 2020). For the research study, consumers constituted those individuals who were between the ages of 18 and 65, and who purchased products via same-day delivery mobile apps in the past year. The population for the research study was therefore approximately 24.5 million South African consumers (O'Dea, 2020).

A subset of the population, which is the actual focus or target of the research inquiry, is referred to as the target population (Saunders et al., 2019: 295). The target population for the research study comprised South African consumers residing in Gauteng, KwaZulu-Natal or the Western Cape provinces of the country. These provinces were selected for the purpose of the research study as they are considered the business capitals of South Africa, are highly urbanised, have the highest per-capita income levels in the country and are the most densely populated (Gauteng: 15.8 million, KwaZulu-Natal: 11.5 million, Western Cape: 7.1 million) (Statistics South Africa, 2021:

vi). Furthermore, the majority of the grocery-related same-day delivery apps that were available in South Africa, during the time the study was conducted, were widely implemented and used in these three provinces. Although some similar apps were piloted in other parts of the country, they were not in full use in large parts of the country.

The sample for the research study was therefore drawn from South African consumers who were between the ages of 18 and 65, resided in either Gauteng, KwaZulu-Natal or the Western Cape provinces of South Africa and made use of at least one same-day delivery app in the past year. The sample of the study comprised 485 South African consumers. The complete profile of the respondents who formed part of the research study is reported in Chapter 6, section 6.2.

The techniques and methods used to draw a sample from the target population are described next.

5.2.4.1 Sampling techniques and methods

Sampling techniques are divided into two types, namely probability (or representative) sampling and non-probability (or non-random) sampling.

With probability sampling, every element in the population has a known non-zero chance of being selected from the target population, and the chance of being selected is the same for every unit in the population (Saunders et al., 2019: 296; Venter & Van Zyl, 2017: 135). For non-probability sampling, the chance of each unit being selected from the target population is unknown and members are selected from the population in a non-random manner (Saunders et al., 2019: 296; Venter & Van Zyl, 2017: 135). Non-probability sampling, according to Malhotra (2019: 335), relies on pragmatism and the objectivity of the researcher rather than the coincidental selection of sample elements.

Table 5.2 tabulates the conditions favouring the use of probability and non-probability sampling.

Table 5.2: Conditions favouring the use of probability and non-probability sampling

Factors	Probability sampling	Non-probability sampling
Nature of research	Conclusive	Exploratory
Relative magnitude of sampling and non-sampling errors	Sampling errors are larger	Non-sampling errors are larger
Variability in the population	Heterogeneous (high)	Homogeneous (low)
Statistical considerations	Favourable	Unfavourable
Operational considerations	Unfavourable	Favourable
Time considerations	Unfavourable	Favourable
Cost considerations	Unfavourable	Favourable

Source: Malhotra (2019: 349)

Probability sampling allows the results to be representative of the population and generalisability is consequently possible. Employing a probability sampling technique furthermore minimises the risk of systematic bias, but this sampling technique can be time-consuming, tedious and redundant (Salkind, 2018: 91). Non-probability sampling allows the researcher to select cases quickly, conveniently and cost-effectively and is suitable when time and resources are limited. Non-probability sampling is the preferred technique when the target population is difficult to identify, locate, contact, or the population is small and dispersed over a wide geographical area (Allen, 2017: 1537; Glen, 2021). However, due to the inability to control researcher bias in case selection and because confidence levels and margins of errors cannot be calculated, the degree of generalisability in non-probability sampling is questionable (Allen, 2017: 1538; Glen, 2021).

For the purpose of the research study, a non-probability sampling technique was deemed appropriate. Given the size of the population, the absence of an accurate sampling frame and the limited time and resources available to complete the research study, it was unlikely that all South African consumers could be reached and included in the study equally. While employing a probability sampling technique would have enhanced the representativity of the sample and the generalisability of the results, the use of convenience sampling was deemed more viable in addressing the research objectives as outlined in Chapter 1 (section 1.5) and section 5.2.1 above.

The different probability and non-probability sampling methods a researcher can adopt are presented in Figure 5.3.

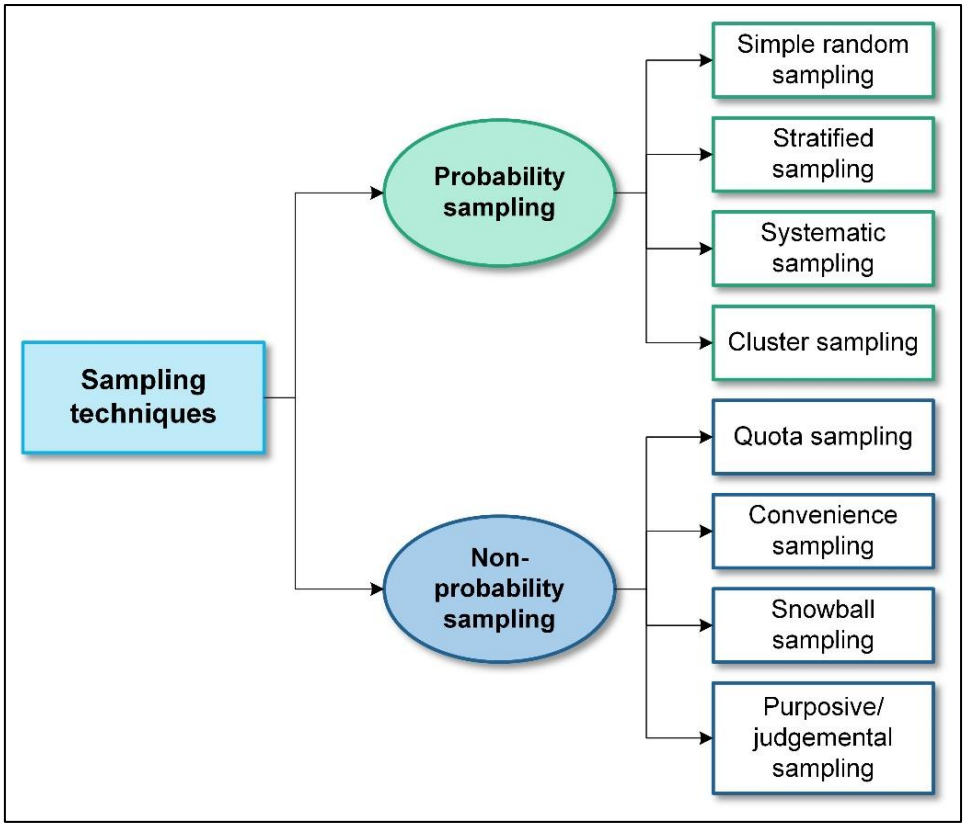

Figure 5.3: Sampling techniques and methods

Source: Malhotra (2019: 335); Saunders et al. (2019: 297)

Convenience sampling, a form of haphazard sampling, entails the random selection of cases because they are easily available (or most convenient) to obtain (Saunders et al., 2019: 324). Participants are therefore chosen based on ease of access or availability (Zickar & Keith, 2023: 316). The fundamental feature of convenience sampling is that participants are selected based on their propensity to respond to the survey itself. The challenge of convenience sampling is that the population to which the sample can be compared is unclear. However, with screening questions, online convenience samples can be targeted to meet specific criteria (e.g. people who use same-day delivery apps), though the problem of generalisation remains (Zickar & Keith, 2023: 316).

The advantages and disadvantages of convenience sampling are tabulated in Table 5.3.

Table 5.3: Advantages and disadvantages of convenience sampling

Advantages	Disadvantages
• Easy to execute with few rules governing how the sample should be collected • Least expensive and least time-consuming of all the available sampling techniques • Enables the researcher to achieve the necessary sample size in a relatively fast and cost-effective manner • Sampling units are accessible, easy to measure and cooperative • Useful in exploratory research to generate ideas, insights and hypotheses or propositions • Allows the researcher to gather useful data and information that would not have been possible using probability sampling, which requires formal access to lists of populations	• Selection bias, such as respondent self-selection • Not representative of any definable population • Generalisability is not possible • Can result in over- or under-representation of specific groups within the sample

Source: Du Plessis (2018: 178); Lærd Dissertation (2012); Malhotra (2019: 337)

Convenience sampling allows for greater control over the cases or units selected to be included in the sample and is more appropriate as particular elements of the population are conveniently selected. As a non-probability sampling technique, convenience sampling limits the ability of a researcher to make valid generalisations beyond the elements included in the sample (Daniel, 2012: 11). The primary objective of the research study, however, was not to generalise the findings, but rather to develop a conceptual model combining the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps. Since the selection of cases was not merely made based on the availability of respondents, selection bias is reduced. Sample bias was furthermore addressed by ensuring that a representative sample of participants was obtained (refer to the discussion in section 5.2.4.2 below).

By using convenience sampling, the researcher can conveniently select participants and conduct a large number of interviews within a relatively short amount of time (Van Niekerk, 2020: 214). As the research study sought to collect 400 questionnaire responses, convenience sampling was deemed to be well suited.

The process of selecting a representative sample for the study is addressed in the next section.

5.2.4.2 Selecting a sample size

After defining the sampling procedure, the size of the sample must be determined. The sample size should be suitable to support the research purpose and design of the study effectively (Hefer, 2017: 131) and be able to yield adequate responses for the statistical analyses to be conducted to reach the set objectives of any given study. The sample size depends on several factors, such as the basic features found in the studied population, the nature of the research, the number of variables, the statistical requirements, the sample sizes used in previous studies, incident rates, completion rates, resource constraints and the anticipated reliability and accuracy of the results (Malhotra, 2019: 333; Thusi, 2018: 72).

Several recommendations also served as a guideline in determining the sample size. Stevens (2009: 164) recommends a ratio of 15 observations to 1 (15:1) observed variable (i.e. 15 x 14 constructs[3] = 210); Bentler and Chou (1987: 78) recommend at least 5 cases per parameter estimate including error terms and path coefficients (i.e. 5 x 70 items used in the research instrument = 350). For correlation analysis, the general rule of thumb is no less than 50 participants (Van Voorhis & Morgan, 2007: 48). It is furthermore suggested that N > 50 + 8*m* (where *m* is the number of constructs, including moderators) for testing multiple correlations (i.e. 50 + 8(14) = 162). Large samples undoubtedly represent the characteristics of the population from which they are derived more accurately, increase power and decrease estimation errors (Van Voorhis & Morgan, 2007: 45).

To have a 95% confidence level in the data obtained, a population of more than 1 million requires a sample size of at least 384, as calculated using the following formula, where N is the sample size, *z* is the z-score for the desired confidence level (1.96 for 95% confidence), *p* is the estimated proportion of the population that has the characteristic of interest (if *p* is unknown, use 0.5), and *e* is the desired margin of error (i.e., 0.05):

$$Sample\ size = \frac{\frac{z^2 \times (1 - p)}{e^2}}{1 + (\frac{z^2 \times p\ (1 - p)}{e^2 N}}$$

[3] 11 independent constructs, plus 1 dependent construct, plus 2 moderators equals 14 constructs.

According to Leedy and Ormrod (2016: 166), however, for a population size of more than 5 000, the population size becomes irrelevant in selecting a suitable sample size and a sample size of 400 is deemed adequate for statistical analyses. A sample size of 485, as achieved in the research study, was therefore deemed fit for various reasons. Firstly, a sample larger than 200 was considered adequate to conduct structural equation modelling (SEM). Secondly, for correlation analysis, a minimum sample size of 162 was required. Thirdly, a review of previous research related to the adoption of on-demand service delivery mobile apps used sample sizes ranging between 195 and 462 (e.g. Elango et al., 2019: 1 (n = 392); Erwanti et al., 2018: 9 (n = 334); Flores & Castaño, 2020: 25 (n = 462); Karulkar et al., 2019: 146 (n = 253); Lee et al., 2019: 1 (n = 340); Mensah, 2019: 29 (n = 255); Muangmee et al., 2021: 1304 (n = 402); Rasli et al., 2020: 679 (n = 389); Yapp et al., 2018: 105 (n = 195)).

The 485 completed questionnaires obtained in the research study were therefore considered highly satisfactory for achieving adequate statistical power to detect effects by performing CFA, SEM, correlation analysis and moderation analysis.

5.2.5 STEP 5: THE RESEARCH INSTRUMENT

Developing the research instrument for data collection is the fifth stage in the research process, as shown in Figure 5.1.

As previously discussed, the research study adopted a quantitative, exploratory and descriptive research design. Non-experimental survey research was employed because it is associated with a post-positivistic, deductive and quantitative research approach and is often used in exploratory and descriptive research (Saunders et al., 2019: 193). Survey research permits researchers to make inferences and propose possible explanations for relationships between constructs and produce conceptual models (Saunders et al., 2019: 194). Moreover, in survey research, researchers have control over the research process and large amounts of data about constructs can be collected. The findings generated from survey research are statistically representative of the whole population (Saunders et al., 2019: 194).

Given that the research study sought to determine the factors that influence South African consumers' continuance acceptance of same-day delivery apps, it was necessary to gather data from a large population to identify potential relationships between the constructs. Therefore, using a questionnaire to ask specific questions was deemed the most appropriate method for data collection. Questionnaires tend to be used for descriptive or exploratory research. Descriptive

research enables the researcher to identify and describe the variability in different phenomena, whereas exploratory research allows the researcher to examine relationships between variables (Saunders et al., 2019: 505).

More specifically, an online, web-based self-administered questionnaire was administered. A self-administered questionnaire is specifically designed for participants to complete at their own convenience without any direct involvement from the researcher. Online self-administered questionnaires are easily distributed to several respondents and often allow anonymity (Du Plessis, 2018: 176). Web-based surveys are considered a more technologically advanced version of the mail survey and have become an increasingly popular method to collect data (Venter & Van Zyl, 2017: 139). A detailed description of the data collection process will be given in section 5.2.7 below.

To achieve the specific research objectives of the study and capture rich data, a well-designed research instrument must be formulated (Saunders et al., 2019: 505). The development process that was followed to compile the research instrument (see Annexure D) is presented in Figure 5.4 and discussed in more detail below.

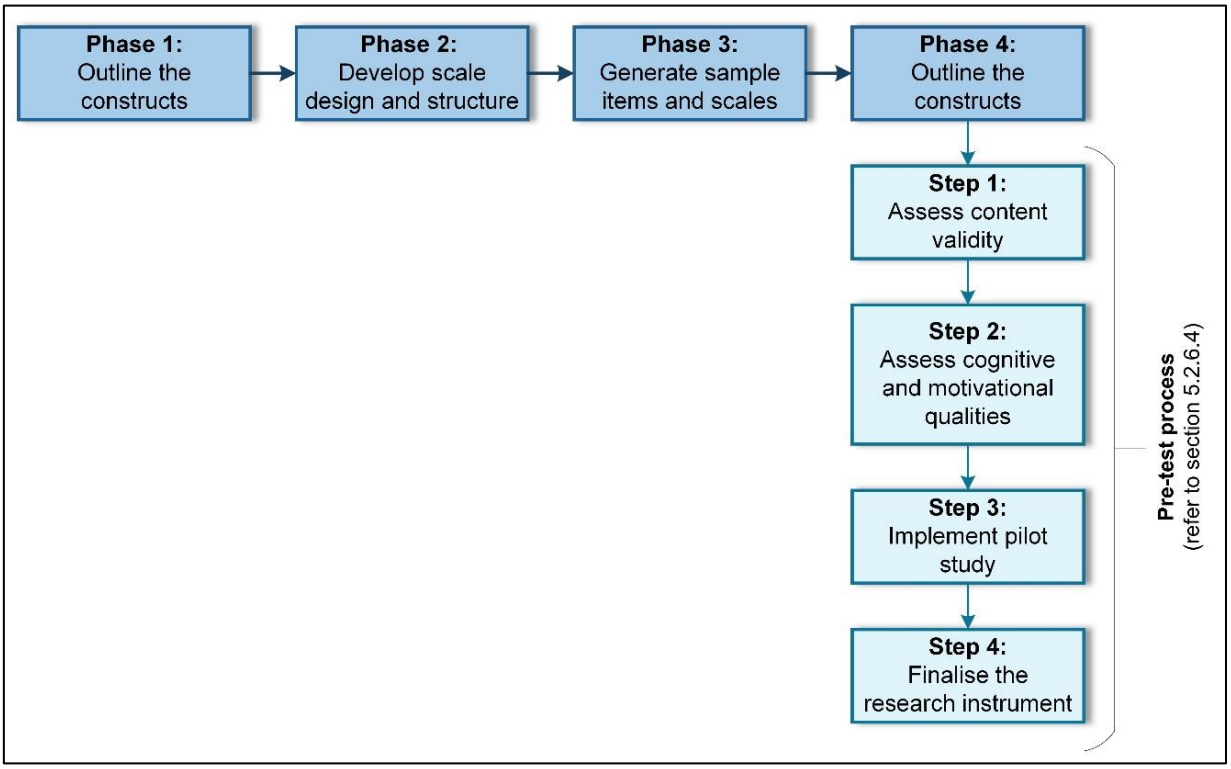

Figure 5.4: Instrument development process

Source: Adapted from Barry et al. (2011: 98)

5.2.5.1 Phase 1: Outline the constructs

The first step in the instrument development process is to outline the constructs with the aim of gaining a comprehensive understanding of the constructs as well as their theoretical properties. The conceptualisation of constructs is essential for valid empirical results and interpretation, and the importance of this step cannot be overstated (Du Plessis, 2018: 180). Barry et al. (2011: 100) posit that researchers should have clearly defined ideas about what constitutes the construct's characteristics, which should ideally be based on published literature and validated theories. It is crucial for researchers to exercise caution in determining what to include (or exclude) from the construct domain since instruments that are too narrow may overlook significant aspects, while overly broad constructs may include inessential aspects from other domains that are extraneous to the research study (Du Plessis, 2018: 180).

DeVellis (2012: 106) states that theory or literature aids in clarifying constructs and therefore serves as the basis for grounding the theory of a construct. As discussed in section 5.2.2 above, an extensive literature search was conducted to develop an in-depth understanding of the context of the research study, as well as to determine the scientific and methodological rigour of the UTAUT2 Model and constructs that underpin the research study. The systematic evaluation of existing literature highlighted key constructs, validated in previous scholarly research, as antecedents that could influence consumers' behavioural intention to accept and use new technology. The operational definitions of the constructs used in the research study were conceptualised in Chapter 4. The operational definitions and keywords for each construct are furthermore detailed in Annexure C.

5.2.5.2 Phase 2: Develop scale design and structure

After determining what is truly being measured, the researcher must delineate the format of items, tasks, or questions, select the response format or conditions for responding and outline the types of scoring procedures (Barry et al., 2011: 101). It is furthermore important to consider the data analysis plan and the appropriate response scale to facilitate those analyses. Consequently, the level of data (or scales of measurement) used must enable statistical analysis. Matters such as the choice of the response format, the scales of measurement, the statistical analyses required, the validity of existing scales and items and the size of the item pool should be taken into consideration during phase 2 of the instrument development process (see Figure 5.4).

Most self-administered research instruments include a combination of open-ended and closed questions. Open-ended (or unstructured) questions allow respondents to give answers in their own words, whereas closed (or structured) questions are forced questions eliciting a response between two or more alternatives. Closed questions are generally quicker and easier to answer, make statistical comparisons easier and reduce interpretation errors (Saunders et al., 2019: 519). Closed questions were used in a structured and systematic manner for ease of data collection, statistical analysis purposes, comparability of answers and due to the nature of the research study.

Various types of closed questions can be adopted, such as (1) a list or multiple-choice questions allowing respondents to choose one or more responses from a list of alternatives, (2) category questions in which each respondent's answer can fit only into one category, (3) dichotomous questions allowing respondents to only choose between two alternatives, such as yes and no, (4) ranking questions asking respondents to place things in a specific order, for instance order of importance, (5) rating or scale questions generally to collect opinion data where respondents rate the importance, frequency or significance on a continuum, (6) quantity questions requiring respondents to provide a numerical or factual response, such as the year in which they were born and (7) a matrix or grid question enabling the respondent to record the responses of two or more similar questions at the same time (Malhotra, 2019: 301-303; Saunders et al., 2019: 519-528; Venter & Van Zyl, 2017: 142).

In the development of the research instrument, the scales or levels of measurement should also be considered as each measurement scale has certain properties which determine the appropriateness for certain statistical analyses to be conducted. "Levels [or scales] of measurement reflect the way in which outcomes are measured or assessed" (Salkind, 2018: 95). It is crucial to ensure that the required statistical analyses can be conducted with the specific response format to achieve the objectives of the research study.

Table 5.4 describes the four types of measurement scales and lists the extent of statistical analysis which each dataset allows.

Table 5.4: Scales or levels of measurement

Scales/levels of measurement		Explanation	Statistical analysis
Non-interval scales	**Nominal data** *(categories)*	Classifies data into distinct categories of individuals, objects or responses based on a common property or characteristic, and without taking cognisance of any underlying order or rank. It is used for variables that are categorical but have no particular order. For example gender, province, ethnic group, religious group.	Percentages, mode, chi-square, binominal test
	Ordinal data *(category and order)*	Classifies data into distinct categories based on rank order. Variables are ordered in a direction of magnitude, but the differences between each category are not quantifiable. It is thus possible to determine whether an object has more or less of a characteristic. For example, measuring economic status, educational level or expertise.	Percentile rank, median, Spearman's rank-order correlation, Friedman ANOVA
Interval scales	**Interval data** *(category, order and spacing of equal intervals)*	Offers standard and equal units of measurement by indicating the degree or amount of difference in relation to the spread of variables. Exact differences between categories are given, but there is no true zero point in the interval data. For example, temperature.	Range, mean, standard deviation, Pearson product-moment correlations, t-tests, ANOVA, regression, factor analysis
	Ratio data *(category, order, spacing of equal intervals and a zero point)*	Allows for ordered scaling where the difference between two measurements involves a true zero point – the intervals are always measured from a zero point. For example, age, income and weight.	Geometric mean, harmonic mean, coefficient of variance

Source: Frankfort-Nachmias et al. (2015: 125-129); Leedy and Ormrod (2016: 93); Malhotra (2019: 243-248); Salkind (2018: 96); Venter and Van Zyl (2017: 145); Walter (2019: 218-219)

Certain variables can be treated as representing different levels of measurement and do not necessarily fall within one category only. Ratio data is the highest level of measurement, descending through interval and ordinal to nominal data, the lowest level of measurement. A variable representing a high level of measurement, such as ratio data, can also be treated as representing a lower level of measurement (Babbie, 2014: 146). Consequently, the level of measurement a researcher seeks is determined by the analytical uses planned for a given variable, keeping in mind that some variables are limited to lower measurement scales. If the researcher wishes to use a specific variable in a variety of statistical procedures to reach the objectives of the research project, the study and research instrument should be designed to achieve the highest level of measurement (Babbie, 2014: 147). However, high measurement scales are not necessary for all research studies.

To achieve the primary objective of the research study – to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model – an interval scale was deemed appropriate to conduct the required statistical procedures. Interval data allow statistical analyses that are not possible with nominal or ordinal data and reflect equal distances among adjacent points (Leedy & Ormrod, 2016: 93). A 5-point Likert scale question, which can be treated as interval or ordinal data (Wu & Leung, 2017: 527), was adopted to assess the rank and order of importance of various constructs under investigation, explore the underlying relationship between constructs, as well as investigate the construct(s) with the strongest correlation with the dependent variable. An interval measurement scale will not only allow for nominal and ordinal data to measure percentages, mode, chi-square, median, correlations and ANOVA, but will also allow for factor analysis and SEM, which was required to achieve the primary objective of the research study. Table 5.5 summarises the response formats and measurement scales used in the study's research instrument.

Table 5.5: Response format and measurement scales per question in the research instrument

Question		Response format	Explanation	Measurement scale
Screening questions (Questions 1 – 2)		Dichotomous question	Yes/No	Nominal
Section A	**Question 3**	Multiple-choice question	Select all that applies	Nominal
	Question 4	Rating or scale question	5-point Likert scale; "frequency" scale	Interval
Section B, question 5 Section C, question 6		Rating or scale question	5-point Likert scale; "agreement" scale	Interval
Section C, question 7		Rating or scale question	5-point Likert scale; "frequency" scale	Interval
Section D	**Question 8**	Category question	Female; Male; Prefer not to say; Other	Nominal
	Question 9	Category question	Before 1930; 1930-1949; 1950-1969; 1970-1989; 1990-2000; 2001-2003	Nominal
	Question 10	Quantity question	Current age (in years), e.g. 32	Nominal
	Question 11	Category question	Gauteng; KwaZulu-Natal; Western Cape; Prefer not to say; Other	Nominal
	Question 12	Category question	Asian; Black; Coloured; Indian; White; Prefer not to say; Other	Nominal

Note: The research instrument is included in Annexure D

Source: Author's own compilation

The scales in the research study consisted of four to nine items, depending on the construct, and totalled 70 statements. To measure these statements, previously validated 5-point Likert scales were used. Participants were asked to indicate their level of agreement or disagreement, with options ranging from strongly disagree (1) to strongly agree (5) for Section B (question 5) and Section C (question 6). In Section A (question 4) and Section C (question 7), a 5-point Likert scale measuring frequency.

One important consideration when developing response scales should be the respondents' ability to meaningfully discriminate between options (Barry et al., 2011: 100). To allow for variance, a Likert scale including at least five response options is preferable (Barry et al., 2011: 100). A Likert scale is a type of rating scale where respondents are asked to express their level of agreement or disagreement, or the frequency of their use, regarding specific statements, with particular statements ranging from least to most. Rating questions, such as Likert scales, are appropriate to collect opinion data (Saunders et al., 2019: 523) and were therefore deemed appropriate for the purpose of the research study. Respondents generally find Likert scale-type questions easy to understand, making them suitable for survey research (Malhotra, 2019: 267). Section A (question 3) was in the form of multiple-choice questions, and the screening questions (questions 1 and 2) were dichotomous questions eliciting a 'yes' or 'no' response from respondents; Section D consisted mostly of categorical questions in which a respondent's answer can fit into one category only.

The various individual items measuring each of the 11 independent constructs were randomised into one large item pool to avoid biased answers from respondents and to ultimately allow respondents to provide 'top-of-the-head' responses. Once the scale design and structure have been developed, the next step in the research instrument development process is generating the sample items and scales.

5.2.5.3 Phase 3: Generate sample items and scales

The importance of having quality items cannot be understated (Barry et al., 2011: 101). The ultimate goal when writing items or modifying existing items is to build a question or statement that all respondents will understand in a similar manner, can provide a precise response to and be agreeable to answer (Barry et al., 2011: 101). Items should be selected or created with the specific measurement goal in mind (DeVellis, 2017: 109). Typically, items consist of two parts: an item stem and a response scale. The literature offers various basic recommendations to follow when writing item stems.

In questionnaire development, the wording and meaning should be carefully considered to ascertain that valid data can be collected to achieve the research objectives (Venter & Van Zyl, 2017: 147). Questions should be carefully formulated and therefore certain guidelines should be considered when developing questions and items. Statements should be clear, short and simple, and everyday language should be used so that respondents will understand (Kumar, 2019: 232). Trendy expressions, colloquialisms, jargon or technical terms, acronyms, double-barrelled items, leading and presumptuous questions should be avoided (Du Plessis, 2018: 182; Venter & Van Zyl, 2017: 147). Furthermore, negative words or reverse-scored items should be used with caution, as these items could negatively affect the psychometric properties of the measurement scale (Du Plessis, 2018: 182).

Table 5.6 provides some examples of pitfalls in questionnaire construction and problems associated with item writing.

Table 5.6: Pitfalls in questionnaire construction

Problem question	Description	Example
Double-barrelled	Two questions are incorporated into one.	Do you engage in online shopping because it is convenient and easy to use?
Loaded or leading	A question that leads a respondent to answer in a certain direction because of its contents, structure or wording.	You agree that online shopping is convenient, don't you?
Negative	Negative questions are more difficult to understand if asked in a negative sense.	Are you not satisfied with the privacy measures implemented by retailers on online shopping platforms?
Unnecessary detail	Requesting participants to provide specific information instead of using categories or groups.	How long have you been shopping online (in years)?
Ambiguous terms or questions	Questions that contain more than one meaning and can be interpreted differently by different respondents.	Do you find using shopping apps difficult because you are not technologically apt?
Presumptive questions	Questions in which the researcher assumes that respondents fit into a particular category and seeks information based upon that assumption.	What online shopping websites do you use?
Implicit alternatives	An alternative that is not explicitly expressed.	Do you like products to be delivered to your door? As opposed to: Do you like products to be delivered to your door, or would you rather visit the store yourself?

Source: Du Plessis (2018: 182); Hague, Hague and Morgan (2013: 122-124); Kumar (2019: 232-234); Malhotra (2019: 304-307); Venter and Van Zyl (2017: 147); Walter (2019: 165)

In summary, the questions and statements in a research instrument should be clear and understandable, concise, readable and distinct, and reflect the instrument's purpose. Items should be uncomplicated and appropriate for respondents' reading level, and lengthy and complicated sentences should be avoided. Colloquialisms or fashionable expressions that may become outdated in the future, double-barrelled questions and leading questions should furthermore be avoided. Questions must be worded so that the respondent understands their meaning and so that the questions have the same meaning for each respondent, and as intended by the researcher (Frankfort-Nachmias et al., 2015: 225). When constructing or adapting items, researchers should take great care in reducing measurement errors caused by poorly worded items, since the wording of a question plays a vital role in determining the answers given by respondents (Barry et al., 2011: 101).

The research instrument used for the study comprised six parts: a cover letter, screening questions, Section A: general information, Section B: factors influencing consumers' behavioural intention, Section C: behavioural intention and use behaviour and Section D: biographical information. Each of these is explained in more detail below.

- **The cover letter (informed consent)**

A cover letter plays an important role in conveying information about the questionnaire and provide instructions to the respondent (Van Niekerk, 2020: 208), especially in self-administering surveys. The purpose of a cover letter is to explain the purpose of the research and offer instructions to the respondent on how to complete the questionnaire, their rights and anonymity (Saunders et al., 2019: 536). The cover letter (see Annexure D) introduced the study and its purpose and stressed the importance of the study by highlighting the anticipated contribution, theoretically and practically. The cover letter furthermore informed prospective respondents of their rights in terms of withdrawing from the study at any time prior to submitting their responses, that their answers were anonymous, and that the researcher undertook to keep any information provided confidential. Prospective participants were advised on the estimated time that would be required to complete the questionnaire, and same-day delivery apps were contextualised to ensure that prospective respondents fully understood the extent of the research study. Lastly, prospective respondents were informed of the ethical clearance obtained to conduct the research and contact details were provided should they wish to report any unethical behaviour. The prospective respondent was then prompted to consent to participate in the research study by confirming that they understood the study, that their participation was voluntary and that they could withdraw at

any time, that they could not be identified and would remain anonymous and that they were between the ages of 18 and 65 years.

- **Screening questions**

A screening question is generally used to either qualify or disqualify respondents from participating in a research study, depending on how they answer, and the inclusion criteria set out for a specific research study (Survey Monkey, 2023). The screening questions sought to determine two things from the prospective respondent to be eligible to participate in the research study: whether they resided in either Gauteng, KwaZulu-Natal or the Western Cape province of South Africa and whether they used same-day delivery apps.

- **Section A: General information**

The aim of Section A of the research instrument was to investigate consumers' use of same-day delivery apps to establish their worth in the South African consumer market. Section A comprised two questions. Question 3, a multiple-choice question, attempted to elicit from respondents which same-day delivery apps they used to purchase products, by asking respondents to select all applicable options. Question 4 comprised a 5-point Likert scale question, with anchors ranging from never (1) to always (5), to establish participants' frequency of using same-day delivery apps for various reasons. The statements in question 4 were developed by the researcher.

- **Section B: Factors that influence behavioural intention**

Section B of the research instrument sought to determine the factors that influence consumers' behavioural intention to continue using same-day delivery apps. The research instrument included items measuring the seven constructs from the UTAUT2 Model (performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value). It further included items measuring the four exogenous mechanisms identified in the literature as factors that potentially influence consumers' behavioural intention (lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use).

Scales used to measure each of the independent and dependent constructs were adapted from several different studies (refer to Annexure C). Scale items for the seven UTAUT2 constructs included in the conceptual model were adapted from Venkatesh et al. (2012: 178).

Scales for the 'lifestyle compatibility' construct were sourced from Arora and Malik (2020: 112), who examined the antecedents affecting Indian consumers' adoption of mobile apps, Belanche et al. (2020: 9), who examined the phenomenon of food delivery services from the mobile app user's perspective and how consumers' lifestyles are changing because of the convenience provided by these apps, and Cuna (2020: 44), who determined which website design features influence the purchase intentions of consumers in South Africa and the influence of lifestyle compatibility and online shopping attitude. Arora and Malik (2020: 102) as well as Belanche et al. (2020: 8) used a 7-point Likert scale ranging from strongly/totally disagree (1) to strongly/totally agree (7). Cuna (2020: 57), on the other hand, used a 5-point Likert scale. The Cronbach alpha value of the 'lifestyle compatibility' construct in these studies was considered excellent: 0.862 (Arora & Malik, 2020: 104), 0.90 (Belanche et al., 2020: 9) and 0.83 (Cuna, 2020: 45).

The 'perceived risk' construct was built using items from Amaro and Duarte (2015: 76), who explored the factors that affect intentions to purchase travel online, Fortes and Rita (2016: 174), who analysed how privacy concerns about the Internet impacted on consumers' intention to make online purchases, as well as Kaushik et al. (2020: 18), who examined the antecedents and consequences of customers' trust towards mobile retail apps in India. Amaro and Duarte (2015: 68) as well as Kaushik et al. (2020: 14) measured the perceived risk construct by means of a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5); Fortes and Rita (2016: 171) measured the construct using a 7-point Likert scale. The Cronbach alpha coefficients for the construct in Amaro and Durate's study (2015: 70), Fortes and Rita's study (2016: 171) and Kaushik et al.'s study (2020: 15) exceeded 0.70, indicating acceptable internal reliability.

The 'perceived self-efficacy' construct was compiled by combining items from three different studies. Hu and Zhang (2016: 647) investigated Chinese students' behavioural intention to use mobile library apps. Singh et al. (2018: 120) explored the factors that impact m-commerce adoption via mobile apps in Malaysia by investigating the relationship between consumer acceptance, trust and self-efficacy. Lastly, Yul (2014: 78) extended the TAM in an attempt to explore the potential predictors of behavioural intention, including mobile app self-efficacy, towards mobile fitness apps. The construct in Hu and Zhang's study (2016: 646) was measured by a 5-point Likert scale, whereas Yul (2014: 57) used a 6-point Likert scale and Singh et al. (2018: 118) used a 7 -point Likert scale, all with anchors ranging from strongly disagree to strongly agree. The Cronbach alpha score for the self-efficacy construct was 0.92, 0.93 and 0.90 for Hu and Zhang (2016: 648), Yul (2014: 72) and Singh et al. (2018: 119), respectively, representing excellent internal consistency.

The last construct added to the conceptual model – 'attitude towards use' – was compiled by merging items from three studies, namely Venkatesh et al. (2003: 460), Hu and Zhang (2016: 647) and (3) Troise et al. (2021: 683). These items were in line with Cho et al. (2018: 112), Kumar and Mukherjee (2013: 31), as well as Yeow et al. (2008: 193), who used similar items in the context of their studies. Venkatesh et al. (2003: 157), as discussed in depth in Chapter 3, empirically tested an amalgamated model exploring users' acceptance of information technology. As discussed above, Hu and Zhang (2016: 639) investigated Chinese students' behavioural intention to use mobile library apps, and Troise et al. (2021: 664) analysed the main drivers of users' intention to use food delivery apps. A 7-point Likert scale was used in the studies of Venkatesh et al. (2003: 166) and Troise et al. (2021: 669); and a 5-point Likert scale was used in Hu and Zhang's study (2016: 646). A Cronbach alpha value of 0.79 was reported by Venkatesh et al. (2003: 458) for the 'attitude towards use' construct; Troise et al. (2021:672) reported a Cronbach alpha of 0.89, and Hu and Zhang (2016: 646) stated that all constructs under investigation in their study exceeded the minimum acceptable Cronbach alpha value of 0.70, indicating that all constructs were reliable.

All items adopted from pre-validated scales were slightly altered for relevancy to the context of the research study. Refer to Annexure C for a comparative summary of how the original items were adapted for the purpose of the research study.

- **Section C: Behavioural intention and use behaviour**

The purpose of Section C of the research instrument was to determine respondents' behavioural intention towards the continued use of same-day delivery apps (dependent construct). The scale used to measure the dependent variable was adapted from two previously validated scales and items, namely Venkatesh et al. (2012: 178) and Chopdar and Sivakumar (2019: 62). The behavioural intention construct in both studies was measured by means of a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7). The Cronbach alpha of the 'behavioural intention' construct in both studies exceeded 0.80, indicating good internal reliability.

Table 5.7 presents a review of the development scale of each of the 11 independent constructs and dependent construct used in the research study, as well as the questions in the research instrument measuring the specific construct. Annexure C provides a detailed outline of the independent constructs, where the construct is conceptualised, the main keywords identified or taken from the definition and the literature are listed, and the adapted statements used in the research study compared to the original items and scales adopted from previous and related research studies are summarised.

Table 5.7: Development of measurement scale

Construct	Scales *(Adapted from previously validated items and scales)*	Questions measuring the construct
Performance expectancy	Adapted from Venkatesh et al. (2012) [Items PE1 to PE5] and Lee et al. (2019) [Item PE6] In line with Chopdar and Sivakumar (2019), Hew et al. (2015), Okumus and Bilgihan (2014), Miladinovic and Xiang (2016) and Yi et al. (2006)	Q5.9[PE3]; Q5.22[PE1]; Q5.42[PE6]; Q5.50[PE2]; Q5.55[PE5]; Q5.59[PE4]
Effort expectancy	Adapted from Venkatesh et al. (2012) [Items EE1 to EE4] and Chong et al. (2012) [Item EE5] In line with Hew et al. (2015), Lee et al. (2019), Miladinovic and Xiang (2016), Palos-Sanchez et al. (2017) and Roback and Wakefield (2013)	Q5.7[EE5]; Q5.16[EE4]; Q5.29[EE3]; Q5.36[EE2]; Q5.46[EE1]
Facilitating conditions	Adapted from Venkatesh et al. (2012) [Items FC1 to FC4] and Lee et al. (2019) [Item FC5] In line with Hew et al. (2015), Lee et al. (2019) and Miladinovic and Xiang (2016)	Q5.13[FC1]; Q5.21[FC2]; Q5.23[FC4]; Q5.47[FC3]; Q5.63[FC5]
Social influence	Adapted from Venkatesh et al. (2012) [Items SI1 to SI3] and Chong et al. (2012) [Items SI4 to SI6] In line with Leong et al. (2013a:2116) and Leong et al. (2013b: 5612)	Q5.3[SI1]; Q5.12[SI2]; Q5.26[SI3]; Q5.32[SI4]; Q5.38[SI5]; Q5.54[SI6]
Hedonic motivation	Adapted from Venkatesh et al. (2012) [Items HM1 to HM3], Fang et al. (2017) [Item HM4] and Indrawati and Haryoto (2015) [Item HM5]	Q5.6[HM3]; Q5.20[HM2]; Q5.34[HM1]; Q5.45[HM4]; Q5.56[HM5]
Habit	Adapted from Venkatesh et al. (2012) [Items HA1 to HA4]	Q5.2[HA1]; Q5.19[HA2]; Q5.41[HA3]; Q5.52[HA4]
Price value	Adapted from Venkatesh et al. (2012) [Items PV1 to PV3], Gupta and Dogra (2017) [Item PV4] and self-developed [PV5] In line with Gupta and Dogra (2017) and Miladinovic and Xiang (2016)	Q5.8[PV3]; Q5.14[PV2]; Q5.25[PV1]; Q5.62[PV4]; Q5.64[PV5]
Lifestyle compatibility	Adapted from Belanche et al. (2020) [Item LSC1], Cuna (2020) [Items LSC2 and LSC3] and Arora and Malik (2020) [Items LSC4 to LSC9]	Q5.1[LSC5]; Q5.11[LSC6]; Q5.18[LSC7]; Q5.33[LSC4]; Q5.37[LSC8]; Q5.40[LSC3]; Q5.48[LSC9]; Q5.53[LSC2]; Q5.61[LSC1]
Perceived risk	Adapted from Fortes and Rita (2016) [Items PR1 and PR2], Amaro and Duarte (2015) and Kaushik et al. (2020) [Items PR3 to PR8]	Q5.4[PR2]; Q5.15[PR8]; Q5.17[PR3]; Q5.28[PR4]; Q5.35[PR5]; Q5.51[PR6]; Q5.58[PR1]; Q5.60[PR7]
Perceived self-efficacy	Adapted from Hu and Zhang (2016), Singh et al. (2018) and Yul (2014) [Items PSE1 to PSE5]	Q5.10[PSE1]; 5.24[PSE3]; Q5.30[PSE2]; 5.44[PSE4]; Q5.49[PSE5]
Attitude towards use	Adapted from Venkatesh et al. (2003) [Items ATT1 to ATT3], Hu and Zhang (2016) [Item ATT4] and Troise et al. (2021) [Items ATT5 and ATT6]	Q5.5[ATT2]; Q5.27[ATT1]; Q5.31[ATT4]; Q5.39[ATT3]; Q5.43[ATT5]; Q5.57[ATT6]

Construct	Scales *(Adapted from previously validated items and scales)*	Questions measuring the construct
	In line with Cho et al. (2018), Hu and Zhang (2016), Kumar and Mukherjee (2013), Troise et al. (2021) and Yeow et al. (2008)	
Behavioural intention	Adapted from Venkatesh et al. (2003, 2012) [Items BI1 to BI3], Chopdar and Sivakumar (2019) [Items BI4 and BI5] and self-developed [Item BI6]	Q6.1 to Q6.6[BI1 – BI6]

Source: Author's own compilation

- **Section D: Biographical information**

Section D of the research instrument elicited the demographic information of respondents by asking structured questions relating to the respondents' gender, age, residing province and ethnic orientation. A demographic profile was included for non-comparative purposes and merely as an indication of completeness and representativeness. Section D of the research instrument was furthermore required to assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps (empirical research objective 7). Moreover, the conceptual model theorised that generational cohort and gender significantly affect the relationship between the independent constructs and behavioural intention (empirical research objective 6). As a result, it was necessary to obtain specific demographic information from respondents.

5.2.5.4 Phase 4: Pre-test the scale

The last phase of the instrument development process, according to Barry et al. (2011: 98), is to pre-test the scale developed or adapted in the previous step. Pre-testing generally focuses on evaluating the measurement properties of the research instrument and how these relate to the quality of the data generated by the questions (Caporaso, 2020: 2). Pre-testing allows the researcher to diagnose and remediate issues with questions or items that influence the ability to measure constructs of interest. Although various pre-testing processes and methods are available to the researcher, the pre-test process of Barry et al. (2011: 98) (Figure 5.5) was adopted for the research study:

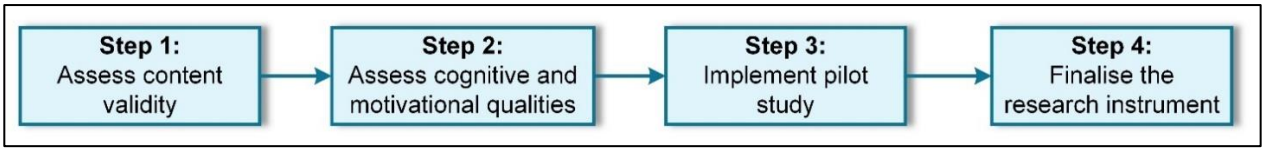

Figure 5.5: Pre-test process

Source: Adapted from Barry et al. (2011: 98)

5.2.5.4.1 Step 1: Assess content validity

The first step in the pre-test process, as proposed by Barry et al. (2011: 98), is to assess the content validity of the scales. Content validity, or face validity, is a subjective but systematic evaluation of how well the elements in a research instrument represent the theoretical construct under investigation (Du Plessis, 2018: 184; Malhotra, 2019: 278). Content validity involves examining whether the scale items adequately cover the entire domain of the construct being measured (Malhotra, 2019: 178), and is used early in the development process before formal pre-testing of the instrument takes place (Caporaso, 2020: 5). Barry et al. (2011: 102) propose that knowledgeable people who are regarded as experts in the field being investigated review the initial questions, items and scales to determine the clarity and relevance of items to the construct being measured. An expert review was consequently used to test for content validity in an attempt to finalise the substantive content of the scale.

An expert review, according to Caporaso (2020: 5), is "… a method whereby survey content is evaluated by experts who give their assessment of how questions will perform and/or how they should be revised". Expert reviewers are generally subject matter specialists who are familiar with the topic under investigation. The rationale for eliciting expert feedback, according to Barry et al. (2011: 102), is to maximise item appropriateness and examine the extent to which proposed items cover all potential constructs. Expert reviewers can furthermore provide insight into alternative ways of measuring the phenomena that were not operationalised.

For the purpose of the research study, 25 candidates were selected and approached to form part of the expert review panel. They were chosen based on their field of knowledge, experience with regard to the conceptual model and their biographical profile, to increase the content validity of the research instrument. From the 25 experts who were approached, 13 responses were received. Table 5.8 collates the biographic profile of the candidates who agreed to expertly review the initial research instrument.

Table 5.8: Biographic profile of expert review panel

No.	Gender	Age category	Highest qualification	Ethnic orientation	Area of speciality
1	Male	51-60	Doctoral degree	Black	Mobile marketing
2	Female	41-50	Doctoral degree	White	Employment relations management; instrument development
3	Male	18-30	Doctoral degree	Black	Marketing: Branding and consumer behaviour
4	Male	41-50	Doctoral degree	Black	Relationship marketing; instrument development
5	Male	41-50	Master's degree	White	Technology and consumer behaviour
6	Male	Older than 65	Master's degree	White	Marketing; instrument development
7	Female	31-40	Master's degree	Coloured	Communications management; consumer behaviour
8	Female	31-40	Master's degree	White	Marketing research; strategic marketing; services marketing; advertising and sales promotion
9	Female	41-50	Master's degree	White	Human resources management; industrial psychology; questionnaire development
10	Female	51-60	Doctoral degree	Black	Consumer behaviour; SME marketing
11	Female	41-50	Doctoral degree	White	Marketing; model development
12	Male	41-50	Doctoral degree	Indian	Marketing; consumer behaviour; brand management; consumer neuroscience
13	Male	51-60	Doctoral degree	Black	Consumer behaviour

Source: Author's own compilation

A total of 13 responses were received from expert reviewers, comprising 6 female and 7 male reviewers. Most of the expert reviewers were between the ages of 41 and 50 (46%), holding a doctoral degree (61.5%) or a master's degree (38.5%) and were ethnically diverse. The expert reviewers' areas of speciality included marketing, consumer behaviour, mobile marketing, model and/or instrument development, or related fields. It is evident that the selected reviewers had the necessary qualifications to validate the research instrument.

The reviewers were asked to assess the research instrument in general, the appropriateness and comprehensiveness of the constructs identified as possible factors that influence consumers' behavioural intention, the clarity and readability of items and their relevance to the specific construct and purpose of the research study. Most of the reviewers indicated that the questions were concise and simple (92%), clear and understandable (100%), did not contain any

terminology, jargon or acronyms that might be unfamiliar to respondents (54%), were relevant to the research objectives and goals of the study (100%) and were well developed (100%). Although 46% of the reviewers indicated that the instrument contained terminology or jargon which respondents might be unfamiliar with, all reviewers stated that these unfamiliar terms were well explained or defined in the survey. Care was taken by the researcher to ensure that potentially unfamiliar terms were either replaced or clearly defined.

Three critical reviewers queried the similarity of the construct 'effort expectancy' and 'perceived self-efficacy'. As theorised in Chapter 4, Venkatesh et al. (2003: 455) excluded the self-efficacy construct, as initially introduced by Compeau and Higgins (1995: 189), because of the construct's conceptual and empirical similarities to effort expectancy in the UTAUT Model. Moghavvemi et al. (2013: 247), however, felt that inexperienced users view new technology as complex, and confidence in a person's own ability to handle new technology has a significant influence on acceptance behaviours. As a result, Moghavvemi et al. (2013: 249) recommend the inclusion of self-efficacy in assessing acceptance behaviour to address the limitation posed by the UTAUT Model to measure individual characteristics. The significance of self-efficacy was furthermore supported by many scholars, even with the inclusion of effort expectancy. It was believed that the inclusion of self-efficacy would provide valuable insight into m-commerce and adoption behaviour research, and therefore the construct was not removed from the research instrument. Refer to Chapter 3, section 3.4.4 and Chapter 4, section 4.2.11 for a detailed discussion.

One expert reviewer cautioned against the use of a 5-point frequency Likert scale in question 3 of the research instrument, arguing that frequency of use was subjective and might be interpreted differently by various respondents. The scale was not changed seeing that a frequency scale is a recognisable question format used in empirical research. The researcher did, however, specify in the specific question that 'regularly' refers to weekly. The researcher also took cognisance of the subjectivity of the scale in analysing and reporting the results.

None of the expert reviewers recommended the removal of any questions or items which they believed were irrelevant to the research study, nor did they recommend any further questions to be included in the research instrument. The reviewers highlighted that, overall, the instrument was well developed, well structured, offered clear and concise instructions, was professionally developed and easy to answer and addressed the research goals and objectives of the study well. A concern raised by three reviewers was that the research instrument was lengthy and could lead to respondent fatigue. The researcher subsequently revised the research instrument to remove

any redundant or repetitive questions. Section A of the research instrument was also condensed and simplified to shorten the research instrument.

With regard to the specific constructs included in the study and research instrument, related to behavioural intention, all 13 expert reviewers agreed that the items were relevant to each of the identified constructs, the items were clear and understandable, and enough items were provided per construct to conduct satisfactory statistical analysis. None of the reviewers recommended that any construct(s) be added or removed from the conceptual model or research instrument and stated that since the constructs were derived from validated measuring instruments, no further amendments were required. Overall, the expert reviewers were satisfied that enough items per construct were given to conduct statistical analysis, the constructs were relevant to the research study and the constructs would measure what was intended.

Apart from the above suggestions, some minor recommendations were made to improve the readability of the items, use synonyms for potentially ambiguous questions/words, reword statements so that they were clearer and include definitions or examples where applicable to ensure that respondents understood the question or context more clearly.

5.2.5.4.2 Step 2: Assess cognitive and motivational qualities

To further strengthen the research instrument, cognitive and motivational qualities were assessed, as per Barry et al.'s recommendation (2011: 98).

Cognitive interviewing focuses on the mental processes respondents use in answering survey questions, and therefore allows the researcher to identify unseen and overt problems in the instrument (Collins, 2015: 14). Cognitive interviewing allows the researcher insight into whether respondents understand all words in the questionnaire, whether all questions are interpreted similarly by all respondents and whether every respondent can mark an answer at each question or scale item (Barry et al., 2011: 102). Consequently, it allows the researcher to establish whether respondents understand each scale item as intended and whether questions can be accurately answered (Barry et al., 2011: 102).

The two most commonly used cognitive interviewing techniques are think-aloud interviewing and probing to expose the participant's thought processes (Collins, 2015: 14). Both techniques involve the researcher asking the respondent how they went about answering the questions in the survey. In the first approach, the respondent is asked to think aloud while answering the questions, to

establish how the respondent understood each of the questions and items in the survey. With the second approach, the researcher asks specific questions or probes about how the respondent set about answering the questions to elicit, but not alter or bias, the respondent's answer or thought processes (Collins, 2015: 15). Each technique can be used separately or concurrently.

For the purpose of the research study, a verbal probing technique was used among a sample of six respondents. Verbal probing, according to Given (2008: 90), occurs after the respondent has completed the questionnaire, with the researcher asking additional questions about how items were interpreted and the basis for respondents' responses. This technique was adopted to avoid altering the way respondents would think about the subsequent question if the researcher probed per question or item as the respondent worked through the questionnaire (Collins, 2015: 15). Respondents were asked to give their interpretation of specific items in the scale, their assessment of the accuracy of their responses, items they were uncertain of how to answer or what was meant by the scale item and their evaluations of the appropriateness of the questions. The researcher furthermore espoused a subset of the think-aloud technique to elicit the thinking process of the respondent when completing the questionnaire. The researcher aimed at understanding why the respondent selected either a high or low response at specific scale items.

A qualitative approach was followed during the cognitive interview process to identify patterns of problems or recurrent themes. The researcher compiled a summary of scale items and respondents' comments to identify patterns or recurrent themes that had to be addressed. The findings of the cognitive interviews were predominantly positive, with all participants expressing their understanding of the expectations, clarity of instructions and ease of completing the questionnaire. Nonetheless, a few participants provided suggestions for enhancing the research instrument.

The most significant suggestions and/or recommendations are summarised in Table 5.9.

Table 5.9: Findings from the cognitive interviews

Instructions and general suggestions	
Suggestion/comment	***Action taken by the researcher***
Instructions/information letter	
Include two consent questions. One asking respondents to indicate whether they understand their rights and the second asking respondents to confirm they are between the ages of 18 and 65 years.	Recommendation **rejected**. Respondents were required to consent to all conditions, and therefore it was deemed unnecessary to include two consent questions.
Remove: "By continuing to the next page, you are opting to participate in the survey." This is asked in the consent question and can therefore be removed from the instructions.	The sentence was removed from the cover letter.
Screening questions	
Question 1: It was unclear why the screening question was asked due to the study being applicable to South Africa and all areas in South Africa should be relevant.	Suggestion **rejected**. The target population of the research study included only the three major metropolitan areas as same-day delivery apps are used mostly in these three provinces. The population of the research study were consumers in South Africa and the study hoped to generalise the findings to the entire population. Refer to section 5.2.4 above.
Question 2: Include Uber, Quench and Dis-Chem as examples of same-day delivery apps.	Suggestion **partially accepted**. Uber was not included, because the research study focused on food- and grocery-related same-day delivery apps offering products that are delivered on the same day on which the order was placed. Uber is a transportation service, which did not form part of the scope of the research study. Quench and Dis-Chem DeliveryD were included.
Question 2: The question was considered leading because only a few retailers offering same-day delivery are given in the question. Consider asking a general question instead and only include some examples in the conceptualisation of same-day delivery apps.	The question and definition were revised accordingly.

Instructions and general suggestions	
Suggestion/comment	***Action taken by the researcher***
Section A: General information	
Question 3: Include other options such as supplies which are not available at the local store or only available online. Such as special equipment, printer cartridges, glue, screws etc.	This question was revised so that respondents indicated which same-day delivery apps they regularly (i.e. weekly) used, instead of asking which category of products participants purchased through same-day delivery apps.
Question 4: Include a statement that same-day delivery apps are used because it is safer in terms of no violence, such as hi-jacking or mugging.	**New item included** "… because it is safer than having to physically go to the store" (item 3.18)
Question 4 (4.2): "To purchase services, such as courier services" was not clear. It was unclear whether the researcher referred to courier services that collect packages from your home to deliver to someone else.	The item was revised to refer to services in general and not include a specific example of a courier service.

Section B: Factors that influence behavioural intention			
No.	***Item***	***Suggestion/comment***	***Action taken by the researcher***
5.3	"People who are important to me think I should use same-day delivery apps."	This statement is not clear.	**Revised** "People who are important to me, such as friends, family, or colleagues, think I should use same-day delivery apps".
5.6	"Using same-day delivery apps is very entertaining."	Is "entertaining" the right word? Perhaps 'convenient'? Same-day delivery apps are a "means to an end", not a game or movie that is entertaining.	**Retained** This statement measured hedonic motivation which focuses on fun and enjoyment. The item was taken from a validated scale and therefore the suggestion was rejected.
5.9	"Using same-day delivery apps increases my chances of achieving things that are important to me."	Unclear. It is important for me to get the products so that I can make food, not necessarily important to be able to do other things while I wait for the products to be delivered.	**Revised** "Using same-day delivery apps allows me to achieve things that are important to me while I wait for products to be delivered."

Section B: Factors that influence behavioural intention			
No.	***Item***	***Suggestion/comment***	***Action taken by the researcher***
5.15	"I believe that the risk of purchasing products/services through same-day delivery apps is very high."	It depends on the retailer. For me, it is riskier to purchase online at some retailers while it is not risky at reputable or well-known retailers.	**Retained** The item was open to interpretation by the respondent. Revising the item would have led to a leading question.
5.16	"My interaction with same-day delivery apps is clear and understandable."	Not clear. Clear and understandable in terms of how to use the app, or whether it is clear to me why I use the app (for which reasons/purpose).	**Revised** "The manner in which I interact with same-day delivery apps is clear and understandable."
5.17	"I do not feel comfortable giving out payment information (such as credit card details) to make a transaction on a same-day delivery app."	This statement is confusing because it is negative and was therefore unsure whether I should mark it at the lower end or higher end of the scale.	**Revised** "I feel comfortable giving out payment information (such as credit card details) to make a transaction on a same-day delivery app."
5.21	"Same-day delivery apps are compatible with other technologies I use (such as tablets or smartwatches)."	This statement does not measure intention to use. These types of apps are usually compatible with other technologies. This is an intellectual question.	**Revised** "It is important that same-day delivery apps are compatible with other technologies I use (such as tablets or smartwatches)."
5.25	"The cost of using same-day delivery apps is reasonable."	Also include a statement asking respondents about their perception that it is more expensive than normal apps or online shopping (cost-related question).	**New item included** "It is more expensive to purchase products through same-day delivery apps than physically going to the store." (Item 5.64)
5.34	"I can save money by using same-day delivery apps by comparing prices offered at different stores."	Same-day delivery apps are generally more expensive, and one cannot compare prices between different stores, depending on which app is used.	**Retained** With certain apps, such as OneCart, price comparisons can be done, and consumers can save money. The item was therefore retained.
5.35	"Using same-day delivery apps is fun."	Using same-day delivery apps is a means to an end, it is not fun using it. It is not a game one plays that is fun.	**Retained** This item measured hedonic motivation which focuses on fun and enjoyment. The item was taken from a validated scale and therefore the suggestion was rejected.

Section B: Factors that influence behavioural intention			
No.	***Item***	***Suggestion/comment***	***Action taken by the researcher***
Section C: Behavioural intention and use behaviour			
Q6	N/A	Include a new item: "I intend to use it more". Same-day delivery apps will become increasingly prevalent.	**New item included** "I intend to use same-day delivery apps more frequently in the near future." (item 6.6)
7.6	Same-day courier services, such as 1Fetch, Fastway and The Courier Guy.	People may confuse this one as couriers may deliver some of the products listed in 7.1 to 7.5. For example, I never use courier services to pick up items from me, but I often get deliveries from stores using these courier services.	**Removed** The item was removed. Products are generally purchased on same-day delivery apps and therefore the reference to services in the survey was removed to avoid confusion.

Source: Author's own compilation

It is evident from Table 5.9 that the cognitive interviews yielded valuable insights. Through these interviews, the researcher was not only able to revise and address challenging items, but the overall comprehensiveness and relevance of the questionnaire was enhanced. From the cognitive interviews, it was realised that respondents use a different frame of reference when answering the questions. Therefore, it was deemed fit to include a question asking respondents to indicate which same-day delivery apps they used. This allowed the researcher to obtain more in-depth information and clarity on why certain items were considered more important to some respondents than to others. Furthermore, the researcher realised during the interviewing process that respondents confused purchasing online with purchasing via a mobile app. It was therefore made clearer and more prominent in the research instrument that the questionnaire focused on purchasing products through same-day delivery mobile apps only.

Once the suggestions and recommendations were implemented, the research instrument was subjected to a pilot study, as discussed in the subsequent section.

5.2.5.4.3 Step 3: Implement pilot study

Step 3 of the pre-test process involved implementing a pilot study.

After the required changes have been made to the research instrument, based on the feedback from the expert reviewers and the cognitive interviews, the refined research instrument must be presented to a sample that is representative of the actual population to emulate the proposed data collection procedures.

A pilot study is a small-scale study designed to test data collection techniques to reduce the likelihood of errors in data collection and recording, as well as to assess the validity and reliability of the data that will be collected (Saunders et al., 2019: 812). The main purpose of a pilot study is to test the feasibility of the study (Frey, 2018: 1253), and refine the questionnaire to ensure the seamless collection of data during the large-scale data collection process. Preliminary analysis of the data collection from a pilot study will allow the researcher to determine the validity and reliability of the measuring instrument, whether appropriate scales are used, whether the collected data will enable the researcher to reach the objectives of the study and provide insight into particular questions which frequently go unanswered (Saunders et al., 2019: 540).

Internal consistency, which can be measured using Cronbach's alpha, was used to determine the reliability of constructs (Bryman et al., 2014: 38). Cronbach's alpha is "… a single measure that

quantifies the extent to which a collection of indicators of a supposed single latent concept are interrelated" (Kamis & Lynch, 2020: 2). Cronbach's alpha measures how closely related a set of items are as a group (Sileyew, 2019: 9). Calculating Cronbach's alpha is beneficial as it provides a unique estimate of the internal consistency or reliability of a scale and can be applied to scales of differing lengths (Allen, 2017: 1415). The reliability will indicate the consistency of the test for any of the scales as well as unbiased estimates of the generalisability of the information to the population (Hefer, 2017: 151). A coefficient alpha of 0.70 or higher is considered indicative of a strong item covariance, suggesting a high degree of internal consistency among the items in a measure (Bryman et al., 2014: 38).

The survey was validated through a pilot test on a sample of 37 individuals who represented the target population. These respondents were excluded from the final results. The pilot study provided an opportunity to assess the questionnaire's validity as well as the expected reliability of the data (Saunders et al., 2019: 540). The results of the pilot study are presented in Annexure E. These results showed all Cronbach alpha values to be greater than 0.70, except for the constructs of facilitating conditions (0.442), price value (0.499) and perceived risk (0.696).

Table 5.10 summarises the problems identified during the pilot study and the corrective measures implemented.

Table 5.10: Summary of problems identified during the preliminary analysis (pre-test) and corrective action taken

Item	Comment/problem	Corrective action
Q3	38 same-day delivery apps were listed in the pilot study and respondents had to select all which were applicable to them. Preliminary analyses showed that of the 38 apps, only 26 apps were used by respondents.	To shorten the length of the question and questionnaire, six same-day delivery apps were removed from question 3. It was believed that a shorter questionnaire would most likely increase the response rate. The following six apps were removed: • CAFU Fuel Delivery & Car Wash: This app was removed because the focus of the study was on food- and grocery-related same-day delivery apps, and this is a service app. • DelForno, ColCacchio, Milky Lane, Nuri Sushi and Galito's: These apps were removed from the list because they were all included on the Uber Eats or Mr D Food app, which were most likely used by consumers. Customers would generally only have one app installed on their mobile phones instead of numerous different apps. The following five apps were retained even though they received no selections in the pilot study: • CartRun: CartRun is only available in certain suburbs in Cape Town, which could be the reason that this app was not chosen by respondents. • Deliveroo: Deliveroo collates local restaurants, grocery stores and takeaways into one convenient app and allows customers to order any products and/or restaurant food from a large number of stores. It is possible that Uber Eats and Mr D Food are more popular than Deliveroo and therefore were not selected. The app was retained on the list to further investigate its significance in the South African market. • Pekkish SA: This app works similar to Uber Eats and Mr D Food in which orders can be placed on the app at various restaurants in a customer's surrounding area. Orders can be delivered or picked up. Pekkish SA is currently only available in Cape Town and could explain why the app was not chosen by the small sample obtained for the pilot study. The app was therefore retained on the list. • Quench: Quench is an on-demand delivery service, delivering drinks, groceries and other essentials directly to the customer. The service is currently only available in Johannesburg, Pretoria, Cape Town and George, which could explain why the app was not selected. The app was retained to further investigate its significance in the South African market. • Stulo: Stulo offers food and items from restaurants and supermarkets on one app, including Checkers, Woolworths, Pick n Pay and Dis-Chem. The reason for no responses to this app is that customers rather use the retailer app specifically, such as Checkers Sixty60, PnP ASAP!, Woolies Dash or Dis-Chem DeliverD to order products. Furthermore, Stulo currently only delivers in Cape Town,

Item	Comment/problem	Corrective action
		Johannesburg, Midrand and Soweto, which could also explain why the app was not selected in the small sample. The app was therefore retained to further investigate its significance in the South African market. The question contained an "other" option. Therefore, respondents could specify any other same-day delivery apps that they might have used in the past which were not listed in this question.
PR Q5.17	The inter-item correlation revealed that item 5.17 had a negative correlation with all other items measuring the perceived risk construct The inter-item correlation mean was also low (0.209). This item had a mean of 3.51, whereas the remainder of the items measuring this construct had an average mean of 2.53 and the Cronbach alpha value for the perceived risk construct was 0.696. [Refer to Annexure E for the results]	**Reason:** After the cognitive interviewing process was completed, the item was changed from "I <u>do not</u> feel comfortable…" to "I feel comfortable …" because respondents were uncertain at which end of the scale to answer this question as it seemed to be confusing (see Table 5.9, section 5.2.5.4.2). **Solution:** Because of the abovementioned change to item 5.17, the item had to be reverse scored. After the item was reverse scored, the item no longer presented with a negative inter-item correlation with other items. Furthermore, the Cronbach alpha value for the perceived risk construct improved from 0.696 to 0.826, the direction of agreement was similar to other items measuring the construct (mean: 2.49), the inter-item correlation increased to 0.352 and no items had to be removed from the construct. The revised item was therefore retained but was reverse-scored during analysis.
FC Q5.13 Q5.21 Q5.23 Q5.48 Q5.65	The facilitating conditions construct revealed a statistical problem as the inter-correlation between the items was low. The following were detected: • The inter-item correlation revealed that item 5.13 had a negative correlation with all other items measuring the construct. • There was no significant inter-item correlation between item 5.21 and item 5.48.	**<u>Item 5.13</u>** **Reason:** Item 5.13 was the original item as used in the validated scale by Venkatesh et al. (2012), with a slight amendment to the original item to include "… such as friends or family members …" to clarify the statement. The addition to the question might have been leading the respondent's answer. **Solution:** To ensure that the item was valid in terms of the construct being measured, and in line with the validated scale used by Venkatesh et al. (2012), the addition of the example was removed and the item was reverted to the original item as provided by Venkatesh et al. (2012).

Item	Comment/problem	Corrective action
	• Item 5.21 correlates with item 5.23. • Item 5.23 correlates with item 5.48. • Item 5.48 correlate with item 5.65. • Item 5.23 possibly measures two underlying constructs. • The Cronbach alpha value for the facilitating conditions construct was unacceptable (0.442). [Refer to Annexure E for the results]	**<u>Item 5.21</u>** **Reason:** After the cognitive interviewing process, a comment was made by a respondent that the item "Same-day delivery apps are compatible with other technologies I use …" did not measure intention to use, as generally, all apps are compatible with other technologies such as tablets and smartwatches. Consequently, the item was revised to "It is important that same-day delivery apps are compatible with other technologies I use." **Solution:** To ensure that the original item and validated scale were used as intended and empirically validated by Venkatesh et al. (2012), the revised item was changed back to the original item as used by Venkatesh et al. (2012), and the example included in the statement ("such as tablets and smartwatches") was removed to avoid leading the respondents' answer. **<u>Item 5.23</u>** **Reason:** Item 5.23 was the original item as used in the validated scale by Venkatesh et al. (2012), with a slight amendment to the original item to include "… such as smartphone capabilities, WiFi access and mobile data …". The addition to the question might have led the respondents' answers. **Solution:** To ensure that the item was valid in terms of the construct being measured, and in line with the validated scale used by Venkatesh et al. (2012), the original item as empirically validated by Venkatesh et al. (2012) was used, without the inclusion of the example. **<u>Item 5.48</u>** *(Item 5.47 in the final research instrument)* **Reason:** Item 5.48 was the original item as used in the validated scale by Venkatesh et al. (2012). **Solution:** The item was retained because of the validated scale adopted and further investigated after the large-scale data analysis was done. **<u>Item 5.65</u>** *(Item 5.63 in the final research instrument)* **Reason:** Item 5.65 was an additional item added to Venkatesh et al.'s validated scale (2012). The item was taken from the studies of Hew et al. (2015) and Lee et al. (2019) to ensure that the construct had sufficient items to conduct statistical analysis.

Item	Comment/problem	Corrective action
		Solution: The item was retained and was further investigated after the large-scale data analysis was done.
PV Q5.34 Q5.60 Q5.66	Items 5.34, 5.60 and 5.66 did not measure the price value construct. Initially, with these three items included, the Cronbach alpha value for the price value construct was 0.499.	**Items 5.34 and 5.60** *(Note: items are no longer in the final research instrument)* **Reason:** Items 5.34 and 5.60 were additional items added to the validated scale used by Venkatesh et al. (2012). Items 5.34 and 5.60 were adopted from Lee et al. (2019). **Solution:** Both items were removed from the research instrument. Upon further investigation of these items, both items measured 'price saving' as opposed to 'price value' as intended by Venkatesh et al. (2012). **Item 5.66** *(Item 5.64 in the final research instrument)* **Reason:** Item 5.66 was a self-developed item that was included in the research instrument after a suggestion was made by a respondent during the cognitive interviewing process (see Table 5.9, section 5.2.5.4.2). The self-developed item that was added to Venkatesh et al.'s validated scale (2012) could have been the reason for the item not correlating with the other items measuring the price value construct. **Solution:** The item was retained for further investigation during the large-scale data collection process and analysis.

Key: Perceived risk (PR); Facilitating conditions (FC); Price value (PV)

Source: Author's own compilation

Four problems were identified during the preliminary analysis of results, as reported in Table 5.10 above. Corrective measures were taken to ensure the reliability and validity of the research instrument. Firstly, to increase the response rate, the questionnaire was shortened by removing various unrelated or unselected same-day delivery apps from question 3. Secondly, the inter-item correlation revealed that item 5.17 from perceived risk (PR3) had a negative correlation with the other items measuring the construct. The item was reverse-scored during data analysis due to the nature of the statement, which improved the construct's Cronbach alpha value from 0.696 to 0.826. Thirdly, the facilitating conditions construct posed various problems as the inter-item correlation was low, insignificant or negative. It furthermore appeared as if various items measuring the facilitating conditions construct were interrelated.

As discussed in Table 5.10 above, various items were retained because a validated scale was adopted from Venkatesh et al. (2012: 178) to measure the specific construct. The slight amendments made to these items to improve the understanding of the items were, however, removed and the original statement as intended by Venkatesh et al. (2012: 178) was reverted to. During the final data collection, which considered the abovementioned corrections and amendments, the Cronbach alpha value for the facilitating conditions construct improved from 0.442 to 0.719.

Lastly, the preliminary results indicated that three items included in the price value construct did not measure price value. Upon investigation, it became apparent that two of the items focused on a price-saving orientation and were, as a result, removed from the research instrument. The third item was retained because the statement was included after a suggestion was made during the cognitive interviewing process to include a cost-related question. After the removal of items 5.34 and 5.60 from the price value construct, the standardised Cronbach alpha value improved from 0.499 to 0.713. The pilot study results confirmed that the remaining items in the research instrument represented the constructs that they were intended to measure. The reliability statistics of the pilot study can be viewed in Annexure E.

Table 5.11 tabulates the Cronbach alpha values of the constructs as represented by the items in the final research instrument (see Annexure D). The Cronbach alpha value for all constructs, as used in the final research instrument, was acceptable at ≥ 0.70, indicating adequate internal reliability.

Table 5.11: Cronbach alpha values for constructs as used in the final research instrument

Construct	No. of scale items	Cronbach alpha value
Performance expectancy	6	0.854
Effort expectancy	5	0.801
Facilitating conditions	5	0.719
Social influence	6	0.832
Hedonic motivation	5	0.847
Habit	4	0.792
Price value	5	0.713
Lifestyle compatibility	9	0.875
Perceived risk	8	0.826
Perceived self-efficacy	5	0.854
Attitude towards use	6	0.838
Behavioural intention	6	0.897

Source: Author's own compilation

The last step in the pre-testing process is to finalise the research instrument for large-scale data collection, which will be discussed in the next section.

5.2.5.4.4 Step 4: Finalise the research instrument

The last step in the pre-testing process is to finalise the research instrument for large-scale data collection. During this step, the corrective action taken during the analysis of the pilot study results is implemented and the research instrument is refined for final data collection. The final questionnaire used for collecting primary data is presented in Annexure D.

The data collection process, step 6 of the research process (see Figure 5.1), is addressed in the following section.

5.2.6 STEP 6: COLLECTING THE DATA

As shown in Figure 5.1, the sixth step in the research process involves administering the research instrument and collecting the data.

As discussed in section 5.2.3.4, a survey research method was applied in the study. Questionnaires, according to Babbie (2014: 262), are used primarily in survey research, which is designed to elicit information that will be useful to obtain statistical data that is quantitatively analysed. Questionnaires can be classified into three categories: self-administered questionnaires, psychological tests and investigator-administered questionnaires (Du Plessis,

2018: 176). Self-administered questionnaires, like the one used in the research study, are designed for respondents to complete independently, without the presence or interference of the researcher. Self-administered questionnaires can be easily distributed to many prospective participants and allow for anonymity (Du Plessis, 2018: 176).

Self-administered questionnaires can be conducted through various channels, such as through the mail or postal surveys, Internet or web-based surveys, SMS (text) surveys as well as by means of physically delivering and collecting the questionnaire. Internet or web-based questionnaires can be administered online either through a website or mobile device (Saunders et al., 2019: 506). An online, web-based self-administered questionnaire was administered in the research study. Web-based surveys are considered a more technologically advanced version of the mail survey and have become an increasingly popular method to collect data (Venter & Van Zyl, 2017: 139).

Babin and Zikmund (2016: 193) highlight three ways in which self-administered web-based questionnaires can be distributed to potential participants: (1) the questionnaire can be included in the body of an e-mail, but this method poses challenges and limits the length of the questionnaire; (2) the questionnaire can be attached to an e-mail, asking the reader to save the questionnaire on their desktop, complete it, save their responses and then return the completed questionnaire to the researcher by means of replying to the initial e-mail; or (3) a hyperlink (or URL link) to the online questionnaire can be included in the body of an e-mail. For the purpose of the research study, the latter approach was adopted, whereby the potential respondent received an e-mail invitation which contained a hyperlink directing the participant to the web-based questionnaire.

The attributes, advantages and disadvantages of using web-based questionnaires are outlined in Table 5.12.

Table 5.12: Attributes, advantages and disadvantages of web-based questionnaires

Attributes	Description
Population for which questionnaire is suitable	Individuals who are computer-literate and who have access to the Internet and e-mail
Confidence that the right person has responded	High if e-mail is utilised
Likelihood of contamination or distortion of respondent's answer	Low due to concerns of unauthorised access by hackers or competitors
Size of sample	Large. Wide geographical reach
Response rate approximation	Variable to low; 10% or lower
Suitable types of questions	Closed questions; not too complex

Attributes	Description
Feasible length of the questionnaire	Limited length (around six to eight A4 pages) to minimise scrolling
Time allocation	Allow respondents two to six weeks to complete the questionnaire, with two reminders sent
Financial resource implications	Costs associated with online survey tools and databases
Data input	Automated, accurate, and real-time data collection
Anonymity of respondent	Respondents can remain anonymous or be known
Special features	Utilisation of streaming media software for visual and animated content

Source: Du Plessis (2018: 193); Saunders et al. (2019: 507-508)

There are certain benefits of using web-based questionnaires for social research: They are less costly than mail surveys and are less time-consuming. They have a high level of respondent anonymity and may encourage honest answers. Interviewer bias is avoided. All major question types can be used in web-based questionnaires, although closed questions are recommended to avoid missing responses. Web-based questionnaires are quickly distributed in a straightforward way to potential respondents. They have a moderate response rate and are suited for targeted samples. Lastly, web-based questionnaires are less hostile and less immediate for respondents as participants can complete the survey in their own time and at their own pace (Frankfort-Nachmias et al., 2015: 206; Venter & Van Zyl, 2017: 139; Walter, 2019: 158).

Possible disadvantages of web-based questionnaires include a lower response rate compared to other data collection methods, they tend to have more missing data, particularly for open-ended questions and multiple reminders are required to reach the targeted sample size. Web-based questionnaires can be prone to provide a biased sample as participation is easy to refuse. The researcher cannot mitigate misinterpreted questions, and probing is also not possible. Lastly, acquiring a representative sample is rarely possible with web-based questionnaires and generalisability is therefore compromised (Venter & Van Zyl, 2017: 139; Walter, 2019: 158).

To mitigate the drawbacks posed by web-based questionnaires, the researcher ensured that the scale items in the research instrument were developed in accordance with the guidelines outlined in the second phase of the research instrument development process (refer to section 5.2.5.2). Care was taken in the development of the web-based questionnaire, and an expert (from a data collection company – Springvale Online) was consulted to ensure that the questionnaire was visually stimulating and properly compiled on the data collection software system to reduce response fatigue and non-response bias. Moreover, the researcher ensured that the instructions provided in the e-mail invitation and introductory letter were clear and concise, aiming to minimise

any ambiguity or confusion. Finally, owing to the possibility of a low response rate, three reminders were sent to the target population in order to encourage their participation in the study.

A self-administered web-based questionnaire was deemed appropriate for the research study, as the target population consisted of individuals who were computer-literate and had access to the Internet and e-mail. Secondly, the database consisted of consumers who were considered active online shoppers, thereby increasing the probability of reaching respondents who used same-day delivery apps, as was required for the purpose of the research study. Thirdly, web-based questionnaires are distributed much faster, they are cost-effectiveness, have a faster turnaround time and they offer more flexibility compared to other data collection methods (Du Plessis, 2018: 192). Fourthly, responses are automatically captured and can easily be downloaded onto the researcher's computer after submission by the respondent. Lastly, respondent anonymity and confidentiality were ensured.

The process and procedures followed to administer the web-based questionnaire to participants are described in the next section.

5.2.6.1 Administering the research instrument

An online marketing and data collection company, Springvale Online, was approached to assist in collecting data for the research study. To achieve the primary research objective of the study, approximately 400 validly completed responses from the three major metropolitans in South Africa, namely Gauteng, KwaZulu-Natal and the Western Cape, were required. This number of responses was required to statistically validate the research instrument and conduct confirmatory factor analysis (CFA) and SEM. Springvale Online offered a large database (≥ 40 000) of potential respondents dispersed across South Africa. Furthermore, they had the capacity, required equipment, hardware, software and knowledge to source responses from a representative sample that met the inclusion criteria of the research study. The researcher, in her own capacity, would not have been able to obtain such a representative sample of consumers from the three provinces in South Africa. Springvale Online was merely utilised to conduct the fieldwork for the research study. Their role was limited to distributing and obtaining valid responses. The coding, validation, cleaning, analysis and interpretation of the data remained the responsibility of the researcher.

An experienced consultant from Springvale Online uploaded the questionnaire, as provided by the researcher, onto the online survey platform that Springvale Online use. Potential respondents on Springvale Online's consumer database were contacted via e-mail, which contained the hyperlink

directing participants to the online, web-based questionnaire. The e-mail invitation sent to the sample population explained the purpose of the research study, the potential contribution, instructions on how to complete the questionnaire, the time required to complete the questionnaire, their right to withdraw from the study, their anonymity in the research process, voluntariness of participation and the confidentiality of their responses. Finally, prospective participants were informed of the ethical clearance obtained to conduct the research study, and contact information was provided should they wish to report unethical behaviour. Refer to section 5.2.5.3 above for a detailed explanation of the information addressed in the cover letter.

The hyperlink to the web-based questionnaire, provided in the e-mail invitation, redirected the participant to the online survey application where they were first prompted to consent to participate in the research study, confirm that they were between the ages of 18 and 65 and confirm that they understood the nature, procedure, benefits, anticipated inconvenience and their right to withdraw from the research study at any point without consequences. As the respondent submitted the completed self-administered web-based questionnaire, Springvale Online's online system automatically recorded their responses. Data were collected during August and September 2021. The raw data were exported to MS Excel and sent to the researcher for verification and analysis. Thereafter, the researcher prepared the data for statistical analysis and reporting, which is discussed in the following section.

5.2.6.2 Preparing the data for analysis (editing, code book and coding)

Before statistical analysis can be conducted on the obtained responses, the data must be prepared for analysis. In preparing the data for statistical analysis, the researcher must select an appropriate statistical software package as a tool to analyse the data, edit the raw data received, create a codebook and code the responses, construct a database, capture the responses and clean the data. The steps are presented in Figure 5.6.

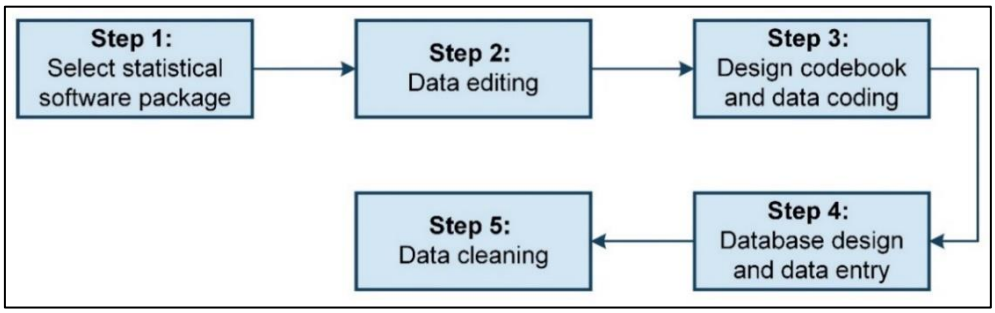

Figure 5.6: Process of preparing the data for analysis
Source: Adapted from Venter and Van Zyl (2017: 158)

The steps in preparing the data for analysis, as presented in Figure 5.6, are briefly explained below.

5.2.6.2.1 Step 1: Select statistical software package

The first decision the researcher must take in preparing the data for analysis is which software package to use to analyse the data (Venter & Van Zyl, 2017: 158). The IBM SPSS, version 28, was used to analyse the data for the research study. SPSS is one of the most popular statistical packages which can perform highly complex data manipulation and analysis with simple instructions. The IBM SPSS plugin, AMOS (version 27), an SEM software, was also used and it extends standard multivariate analysis methods, including factor analysis, regression and correlations.

5.2.6.2.2 Step 2: Data editing

Data editing, according to Malhotra (2019: 410), involves "… a review of the questionnaire with the objective of increasing accuracy and precision of the collected data". During this stage, the completed questionnaires or raw data, are scrutinised to identify ineligibility in terms of poorly recorded items, incomplete responses, misclassification, inconsistencies or ambiguous responses (Kumar, 2019: 376; Malhotra, 2019: 410). Illegibility and incomplete responses are particularly common in questionnaires with many unstructured questions, which is why, during the development of the research instrument, unstructured questions were avoided where possible. Moreover, questions may be incomplete to varying degrees – a few or many questions may be unanswered. For unsatisfactory responses, Malhotra (2019: 410) recommends one of three solutions: return to the field to obtain better data, assign a missing value to incomplete responses, or discard unsatisfactory responses completely. It is therefore imperative that, during this stage, the researcher do preliminary checks for inconsistencies and ambiguity in responses. Data must be understandable for proper coding to take place.

A total of 509 responses were received. Upon review of the raw data, 24 cases were removed from the dataset. One respondent indicated that they resided in the Free State province of South Africa, which fell outside the geographical area of the sample and this case was therefore removed from the dataset. A further four cases were removed as these respondents selected all of the 31 same-day delivery apps listed in question 3, which indicated no variation in the response to the question. There were furthermore several cases (19) that showed very little to no variation across the Likert scale items in questions 5 and 6. As a result, these cases were removed from the

dataset. A total of 485 validly completed responses could therefore be used for statistical analysis purposes. Participant recruiting and data collecting processes were rigorous, resulting in a complete dataset, eliminating the need for missing data treatment strategies.

Once the preliminary editing of the data has been done, the researcher must design the codebook and code the data accordingly.

5.2.6.2.3 Step 3: Design the codebook and data coding

Before capturing data into the selected statistical package, such as IBM SPSS, a codebook must be prepared (Venter & Van Zyl, 2017: 159). A codebook provides guidelines, coding instructions and a set of rules for assigning numerical values about variables in the set (Kumar, 2019: 380; Malhotra, 2019: 413). Advanced statistical packages, such as IBM SPSS, allow for both variable labels and response codes to be entered into the database, which makes the statistical output more understandable and user-friendly (Venter & Van Zyl, 2017: 159). To create a codebook, Saunders et al. (2019: 474) recommend that the data be examined and broad categories be established, broad categories be subdivided into more specific sub-categories reliant on the intended analyses, allocated codes to all categories be meticulous, the actual response be allocated to each category as per the codebook and those categories that need to be combined be given adjacent codes to facilitate recoding.

Once the codebook has been developed, the coding can begin. Coding refers to the assignment of a code, generally a numeric value, to the response to each question (Malhotra, 2019: 411). Coding is dictated largely by two conditions: the way a variable has been measured in the research instrument (levels of measurement), and the way the researcher wants to communicate the findings about the variables (Kumar, 2019: 378). It is important to distinguish between the various levels of measurement (as discussed in section 5.2.5.2 and Table 5.4) since the type of data must be specified in the chosen statistical package (Venter & Van Zyl, 2017: 159). Label variables used in IBM SPSS allow for easier analysis; consequently, the variables in the research study were coded using variable labels, and response codes were used for Likert scale questions.

5.2.6.2.4 Step 4: Database design and data entry

The fourth step of the data preparation process involves designing the database and capturing the data. During this stage, each variable must be created, whether it be in the statistical package being used, or in MS Excel, and the required details must be specified. The codebook provides

the guidelines for creating the database in relation to the variables and measurements. Many online data collection platforms, including the one used by Springvale Online, allow data to be exported into formats compatible with MS Excel or IBM SPSS (Venter & Van Zyl, 2017: 163). Saunders et al. (2019: 576) caution that the following must be ensured when data are captured into the analysis software program: the layout and format of the data must meet the requirements of the analysis software program captured data must be saved and back-ups must be made, data must be checked for errors and corrective measures should be taken (see step 5 below) and weighting cases must be considered especially when stratified sampling is used.

5.2.6.2.5 Step 5: Data cleaning

The last stage of preparing the data for analysis is cleaning the data. Statistical analysis and the subsequent results produced will be deceptive if data-capturing errors have occurred (Venter & Van Zyl, 2017: 164). Data cleaning involves a systematic and widespread checking for uniformity and the treatment of missing responses (Malhotra, 2019: 418). While preliminary checks have been made during the editing of the data (see step 2 above), the checks at this stage of the process are more thorough and extensive because these checks are made by computer, after the data have been captured (Malhotra, 2019: 418). Consistency checks during this stage of the process identify data that are out of range, logically inconsistent, or have extreme values (Malhotra, 2019: 418). In this study, no further cases were removed from the dataset.

Once the data have been edited, coded and cleaned, the statistical processing of data can begin – step 7 of the research process (see Figure 5.1).

5.2.7 STEP 7: STATISTICAL PROCESSING AND ANALYSIS OF DATA (CHAPTER 6)

Step 7 of the research process, as shown in Figure 5.1, involves the statistical processing and analysis of collected data. The empirical findings derived from the collected data will be addressed in Chapter 6. The statistical procedures and analysis methods employed in the research study are presented in Figure 5.7 and then briefly discussed. The statistical processing of the data comprises three stages, each consisting of various steps of statistical analysis, as depicted in Figure 5.7.

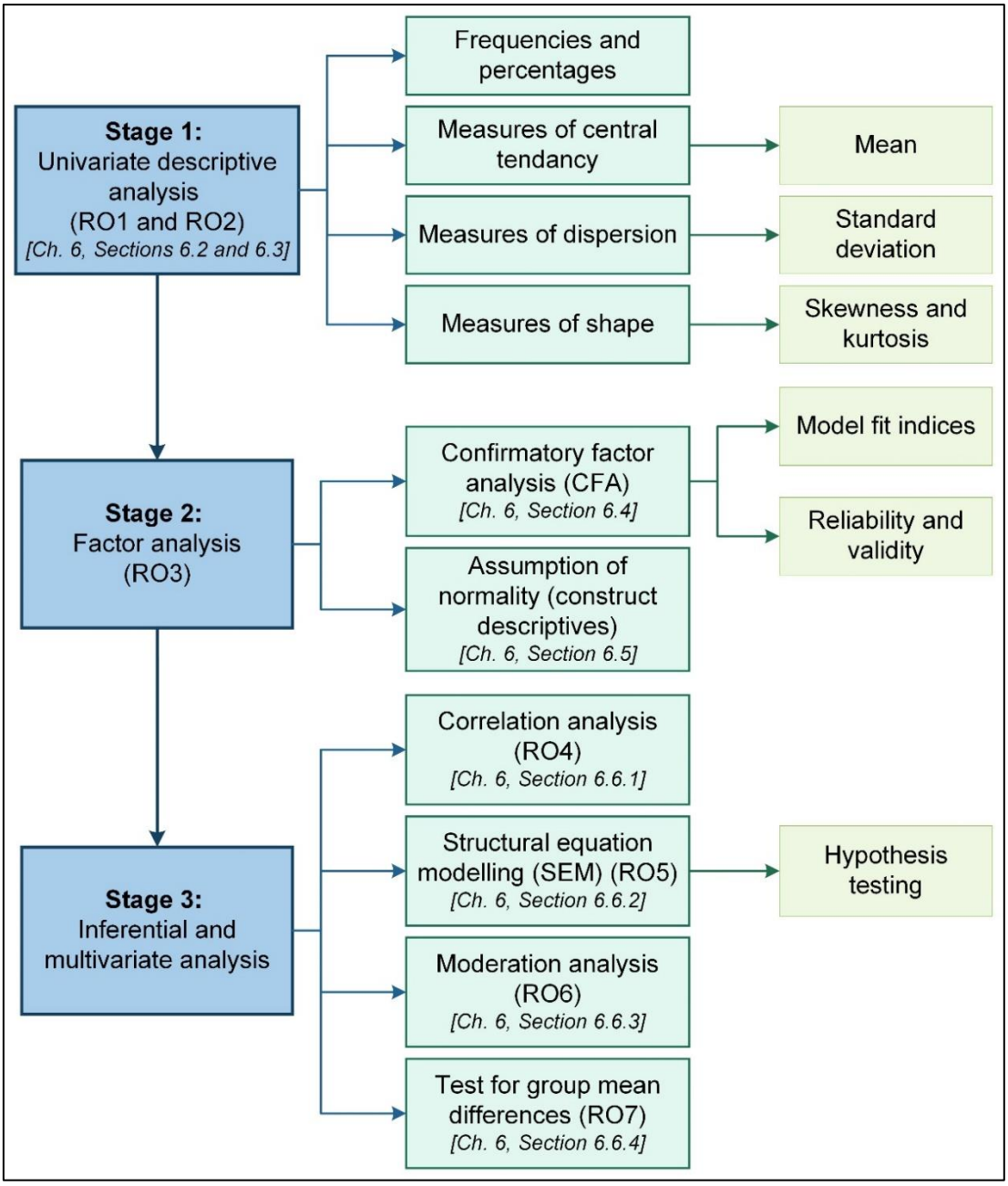

Figure 5.7: Data analysis process and statistical procedures applied in the research study

Source: Author's own compilation

5.2.7.1 Stage 1: Univariate descriptive analysis

Univariate descriptive statistics are generally used to describe the basic features of the variables within a dataset (Babin et al., 2020: 403), and are used to draw comparisons and create descriptions numerically (Saunders et al., 2019: 597). Descriptive statistics focus on describing and comparing data collected from a sample (Saunders et al., 2019: 597), such as describing the age, gender, residing province and ethnic orientation, and reducing information to an

understandable form (Frankfort-Nachmias et al., 2015: 304). Descriptive statistics were used to obtain a quantitative summary of the data as a means of gaining an overall understanding of the sample distribution (Salkind, 2018: 133).

When conducting descriptive analysis, three types of measures can be used to analyse the data and draw conclusions (Nesselroade & Grimm, 2019: 27):

- Measures of central tendency are used to estimate a distribution's central value and are calculated using basic summary statistics such as mean, median and mode (Bryman & Bell, 2011: 319; Salkind, 2018: 134). The centre of a distribution of responses can be found with the use of these statistics. These statistics can give a broad sense of values in the distribution of responses for quantitative investigations that can be viewed as typical or average (Saunders et al., 2019: 599). The most popular way to measure central tendency is with the mean (Kallier, 2022: 154). The mean is analysed in Chapter 6, sections 6.3.1 and 6.5.

- Measures of dispersion or variability are calculated on interval or ratio data and are the degree to which a set of scores are dispersed around the central tendency, most often the mean (Kallier, 2022: 154; Salkind, 2018: 137; Saunders et al., 2019: 601). Measures of dispersion or variability include the range, interquartile range, variance or standard deviation and coefficient of variance (Malhotra, 2019: 443). The standard deviation, which measures the average distance of the values in their distribution from the mean (Neuman, 2014: 401; Van Niekerk, 2020: 241), is assessed in Chapter 6, sections 6.3.1 and 6.5.

- Measures of shape describe the nature of the distribution, or pattern, of the data and are assessed by examining the skewness and kurtosis (Malhotra, 2018: 445). A measure of shape describes how symmetrical or asymmetrical a set of data is (Shaker, 2023: 10). To enable the use of multivariate statistical methods on the data, normality was necessary. The assumption of normality was assessed by measuring the skewness and kurtosis values, which are reported in Chapter 6, sections 6.3.2 and 6.5. Skewness is a characteristic of a distribution that indicates the balance of the distribution of the data, by assessing its symmetry about the mean. Kurtosis is a measure of the relative peakedness or flatness of the curve defined by the frequency distribution (Malhotra, 2019: 445).

The analysis process commenced with an initial investigation of descriptive statistics to determine the profile of consumers that formed part of the research study. A description of the sample features in terms of respondents' personal characteristics (gender, age, residing province and

ethnic orientation) is provided, as well as a discussion of the relevance of same-day delivery apps in the South African consumer market (see Chapter 6, section 6.2). Frequencies and percentages are calculated to summarise the data to develop generalisations of the demographic profile and characteristics of the respondents. The next step of the descriptive statistical analysis involved examining the means and standard deviations of the latent variables regarding a sample of South African consumers to establish the suitability of the individual scale items (see Chapter 6, section 6.3.1). Descriptive statistics were furthermore used to determine the normality of the data by assessing the skewness and kurtosis of the dataset (refer to Chapter 6, section 6.3.2).

5.2.7.2 Stage 2: Factor analysis

During the second phase of statistically processing the data, as shown in Figure 5.7, factor analysis was conducted. Frankfort-Nachmias et al. (2015: 396) describe factor analysis as a statistical technique for grouping several interrelated variables into a small number of dimensions or factors. In general, factor analysis performs several related tasks, such as determining the underlying dimensions or factors that explain the correlation between a set of variables, condensing data by offering a method of explaining variation among variables using newly created variables or factors, defining the substantive content or meaning of the factor that accounts for variation among a larger set of items and helping to identify items that do not fit into any of the factorially derived categories or into more than one of these categories (DeVellis, 2017: 155; Malhotra, 2019: 582).

Factor analysis can be explored through exploratory factor analysis (EFA) and/or confirmatory factor analysis (CFA). While CFA aims to verify whether the number of factors and the loadings of observed variables are consistent with what is predicted based on theory, EFA is used to find underlying dimensions or factors that explain the correlations among a group of variables (Malhotra, 2019: 681). Because preconceived ideas about the underlying dimensions were readily available and supported by theoretical presumptions and reasoning, EFA was not conducted in the research study. The theoretically developed conceptual model (see Chapter 4, Figure 4.1) and underlying theory covered in Chapters 3 and 4 serve as an illustration of these preconceived notions.

CFA was used in the research study to assess if the collected data fit the proposed measurement model and to validate the measurement model by exploring the reliability and validity that is unique to SEM. The selection of fit indices (see Table 5.13 below) and reliability and validity assessments were used to determine the best model fit. Firstly, the model fit was assessed using the

conventional absolute fit indices (CMIN and CMIN/*df*). These indices offer a preliminary assessment of the degree to which an *a priori* model fits the sample data (Kirsten, 2019: 658). The chi-square (CMIN) score represents the degree of discrepancy between the variance/covariance pattern of the data and the model that is being tested. However, chi square is highly sensitive to correlations among observed variables, unique variance and sample size (Hair, Black, Babin & Anderson, 2014a: 578). A combination of several goodness-of-fit indices should therefore be used to assess the model fit (Du Plessis, 2018: 203). These indices are discussed in the next section.

5.2.7.2.1 Goodness-of-fit indices

Goodness-of-fit indices are used to assess the extent to which the empirical data aligns with the theoretical model (Wesolowski, 2018: 2). These indices provide insights into the overall fit and compatibility of the observed data with the proposed theoretical framework. Badness-of-fit indices measure errors or deviations (Malhotra, 2019: 673). Good-fitting models, according to Tabachnick and Fidell (2013: 725), produce consistent results on many different indices. If the results of the fit indices are inconsistent, the model should be re-examined. If the theory compilation was done accurately, the estimated covariance matrix and the actual observed covariance matrix ought to align. The comparison between these two matrices provides an indication of the estimated model fit. The estimated model fit is thus provided by this comparison; the closer these two matrices are to one another, the better the model fit (Van Niekerk, 2020: 229).

Three fit indices were tested in the research study, namely absolute fit, incremental fit and information-theoretic fit. An absolute fit index provides a clear indication of how effectively the researcher's specified model fits or reproduces the observed data (Hair et al., 2014a: 578), and determines which proposed model fits the data the best (Hooper, Coughlan & Mullen, 2008: 53; Kelloway, 2017: 3). The level of improvement in model fit is evaluated without the aid of a reference model; however, an implicit or explicit comparison to a saturated model that accurately replicates the sample covariance matrix may be made (Hu & Bentler, 1999: 2). The model chi-square test (CMIN and CMIN/df), goodness-of-fit (GFI), root mean square error of approximation (RMSEA), standardised root mean square residual (SRMR) and adjusted goodness-of-fit (AGFI), as described in Table 5.13, were applied in the research study to assess absolute fit.

Incremental fit indices, also known as relative or comparative fit indices (McDonald & Ho, 2002: 72), assess the degree to which the estimated model fits in comparison to some alternative baseline model. Incremental fit indices do not use the chi square in its raw form but compare the chi-square value to the baseline model (Hooper et al., 2008: 55). A null model is the most typical

baseline model and it presumes that all observed variables are uncorrelated (Bhanot, n.d.: 142; Hair et al., 2014a: 579; Hu & Bentler, 1999: 2). The normed fit index (NFI), Tucker Lewis index (TLI) and comparative fit index (CFI), as described in Table 5.13, were applied in the research study to assess incremental fit.

Information-theoretic fit indices express the extent to which the present model will cross-validate in future samples of the sample size from the target population (Kirsten, 2019: 661). Akaike's information criterion (AIC) and Bayesian information criterion (BIC), as discussed in Table 5.13, were applied in the research study to assess the information-theoretic fit of the model. Generally, models with the lowest AIC and BIC values are deemed to fit the data better in relation to alternative solutions (Schumacker & Lomax, 2010: 76). The results of the model fit indices are discussed in Chapter 6, section 6.4.1.1 for the original measurement model, and Chapter 6, section 6.4.2.1 for the revised measurement model.

The model fit indices used to assess the measurement model in the research study and the threshold applied in the CFA analysis are discussed in Table 5.13.

Table 5.13: Summary of model fit indices and threshold applied in the research study

Index	Description	Threshold applied
Absolute fit indices provide a clear indication of how effectively the researcher's specified model fits or reproduces the observed data (Hair et al., 2014a: 578) and determine which proposed model fits the data the best (Kelloway, 2017: 3). The level of improvement in model fit is evaluated without the aid of a reference model; however, an implicit or explicit comparison to a saturated model that accurately replicates the sample covariance matrix may be made (Hu & Bentler, 1999: 2). Absolute fit indices include the chi-squared test, GFI, RMSEA and SRMR (Schweizer & DiStefano, 2016: 172).		
Chi square (CMIN)	The chi-square value is a common metric for assessing the overall model fit and assesses the magnitude of discrepancy between the sample and fitted covariance matrices (Hooper et al., 2008:53; Hu & Bentler, 1999:2; Long, 2011: 10). The chi-square test determines if the model fits the population exactly (Harrington, 2009: 51), and forms the basis of many other GIF measures (Kirsten, 2019: 659). A large chi-square indicates a significant difference between the data and the hypothesis, indicating that the data do not fit the hypothesised model (Kallier, 2022: 158).	The absence of statistical significance ($p \geq 0.05$) supports the model (Kirsten, 2019: 569)
Chi square/*df* (CMIN/*df*) (also known as normed chi square)	A significant difference between the observed and implied variance-covariance matrices is shown by a significant chi-square value in relation to the degrees of freedom (*df*). Because the chi-square test has a high sensitivity to sample size and outliers, researchers often use normed chi square (CMIN/*df*) as a metric for absolute fit (Bhanot, n.d.: 142; Gupta & Singh, 2014: 26), as this index might be less sensitive to sample size (Moss, 2016: 3).	≤ 3 (Awang, 2012: 56; Hu & Bentler, 1999: 27)
Goodness-of-fit index (GFI) Developed by Jöreskog and Sörbom (1982)	The GFI value determines the proportion of variance or covariance in the predicted matrix as compared to the observed matrix (Schweizer & DiStefano, 2016: 172) and indicates how closely the model comes to replicating the observed covariance matrix (Hooper et al., 2008: 54). The GFI therefore determines the proportion of variance between the hypothesised model and the observed covariance (Kallier, 2022: 158).	> 0.90 (Awang, 2012: 56; Gupta & Singh, 2015: 10; Schumacker & Lomax, 2010: 76)
Root mean square error of approximation (RMSEA) Developed by Steiger and Lind (1980)	The RMSEA is a metric for estimating population fit (Bhanot, n.d.: 142) and measures how well the model fits the population (Harrington, 2009: 51). Unlike the chi-square test, the RMSEA is less susceptible to sample size but more sensitive to model complexity (Harrington, 2009: 51). Instead of only using a sample for estimation, the RMSEA presents how well a model fits a population. It specifically tries to correct the sample size and model complexity in its computation (Hair et al., 2014a: 579).	< 0.05 - 0.08 (Gupta & Singh, 2015: 11; Schumacker & Lomax, 2010: 76)

Index	Description	Threshold applied
Standardised root mean square residual (SRMR) Developed by Hu and Bentler (1995)	The discrepancy between the correlations in the input matrix and the correlations predicted by the standardised model serves as the foundation for the SRMR (Harrington, 2009: 51). The SRMR is the difference between the residuals of the sample covariance matrix and the hypothesised covariance model SRMR (Hooper et al., 2008: 54).	≤ 0.08 - 0.10 (Hair et al., 2014a: 579)
Adjusted goodness-of-fit index (AGFI) Developed by Jöreskog and Sörbom (1989)	An AGFI corrects the GFI by considering various levels of model complexity and thereby adjusting the ratio of the degrees of freedom used in a model to the total degree of freedom available (Hair et al., 2014a: 581). The AGFI penalises more complicated models and favours those with a minimum number of paths (Hair et al., 2014a: 581).	> 0.80 (Gupta & Singh, 2015: 10; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012)
Incremental fit indices, also known as relative or comparative fit indices (McDonald & Ho, 2002: 72), assess the degree to which the estimated model fits in comparison to some alternative baseline model. Incremental fit indices do not use the chi square in its raw form, but compare the chi-square value to the baseline model (Hooper et al., 2008: 55). A null model is the most typical baseline model and it presumes that all observed variables are uncorrelated (Bhanot, n.d.: 142; Hair et al., 2014a: 579; Hu & Bentler, 1999: 2). Incremental fit indices include the CFI, TLI and NFI indices (Harrington, 2009: 52).		
Normed fit index (NFI) Developed by Bentler and Bonett (1980)	The NFI evaluates the model by comparing the chi square value of the model to the chi square of the null or baseline model (Hair et al., 2014a: 580; Hooper et al., 2008: 55).	≥ 0.90 (Awang, 2012: 56; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012; Newsom, 2018: 2; Schumacker & Lomax, 2010: 76)
Tucker Lewis index (TLI) Developed by Tucker and Lewis (1973)	Although conceptually similar to the NFI, the TLI differs in that it compares the normed chi-square values for the null and specified models, which partially considers model complexity (Hair et al., 2014a: 580). The TLI offers a measure of the relative placement of a substantive model along the continuum (Du Plessis, 2018: 204).	
Comparative fit index (CFI) Developed by Bentler (1990)	The CFI, an improved version of the NFI, evaluates any contradiction between the results of the data and the hypothesised model (Hair et al., 2014a: 580; Kallier, 2022: 158) while adjusting for the issue of sample size (Du Plessis, 2018: 204; Tabachnick & Fidell, 2007). The CFI considers an estimate of non-centrality in the calculation. The non-centrality parameter measures the discrepancy between the population and the tested model to determine the amount of the lack of fit, expressed as one number (Schweizer & DiStefano, 2016: 179).	

Index	Description	Threshold applied
Information theory fit indices express the extent to which the present model will cross-validate in future samples of the sample size from the target population (Kirsten, 2019: 661).		
Akaike's information criterion (AIC) Developed by Akaike (1973)	The AIC is a criterion used to compare the statistical model and make decisions based on how well each one performs given a certain set of data (Kirsten, 2019: 661). The AIC typically favours simpler models when comparing two or more non-nested models evaluated on the same dataset. A lower AIC indicates that the model fits better, has fewer parameters and is more likely to reproduce (Harrington, 2009: 52).	The lower the AIC/BIC value, the better the fit (Kirsten, 2019: 661; Schumacker & Lomax, 2010: 76; Wu, Cheung & Leung, 2019: 8)
Bayesian information criterion (BIC) Developed by Schwarz (1978)	It is a probability ratio measure that identifies the model that is most likely to be correct given the data. BIC is a measure of how well the model fits the data, taking into account the complexity of the model and the size of the sample (Treiman, 2009: 133).	

Source: Author's own compilation

5.2.7.2.2 Establishing the validity and reliability of the model

Reliability and validity are essential to inferences about the quality of research in quantitative research in the social sciences (Saunders et al., 2019: 213). Reliability is a statistical measure to determine the extent to which a scale produces replicable and consistent results if constant measurements are made on the concepts under similar conditions (Kumar, 2019: 273; Malhotra, 2019: 276; Saunders et al., 2019: 213). Approaches to assessing reliability include the test-retest, alternative forms and internal consistency reliability methods. The most common method, internal consistency reliability, is used to assess the reliability of a summated scale where several items are summed to form a total score (Malhotra, 2019: 277). Internal consistency reliability can be measured using various estimators, but the most widely acknowledged measurement of reliability is Cronbach's alpha (Frey, 2018: 853). Cronbach's alpha was applied in the pre-test to determine the reliability of the measuring instrument (refer to section 5.2.5.4.3 above).

Validity refers to the extent to which a questionnaire accurately measures what it is intended to measure (Bryman et al., 2014: 38; Van Niekerk, 2020: 211). Zumbo (2007: 48) defines validity as "… an ongoing process wherein one provides evidence to support the appropriateness, meaningfulness and usefulness of the specific inferences made from scores about individuals from a given sample and in a given context". A research instrument is considered valid if it measures what it was designed to measure. Researchers may assess content validity, criterion validity, or construct validity (Malhotra, 2019: 278). In the research study, the content and construct validity of the research instrument were assessed.

The content or face validity of the research instrument was assessed in the fourth phase of the instrument development process (refer to section 5.2.5.4 above). Expert reviews and cognitive interviews were used to determine the extent to which a specific measure appears to be related to a particular construct. Content validity was therefore assessed before data collection began to ensure that the research instrument covered all areas of the intended research study. Content validity provided evaluative evidence supporting the constructs under investigation and the representativeness of the content.

Construct validity was furthermore measured to evaluate what the scale is actually measuring (Malhotra, 2019: 279). Venter and Van Zyl (2017: 150) contend that construct validity is the degree to which inferences can justifiably be made to the theoretical constructs on which the operationalisations in the study were based. Construct validity is thus established by relating the research instrument to the general theoretical framework within which the researcher conducts

their study, to determine whether the instrument is logically and empirically tied to the concepts and theoretical assumptions employed (Frankfort-Nachmias et al., 2015: 133). Construct validation can be established by means of a logical process in which the researcher suggests the proposition that an instrument measures a certain property – such as behavioural intention, inserts the proposition into a theory regarding the property – such as the UTAUT2 Model, predicts which properties should be related to the instrument and which should exhibit no relation to the instrument, based on theoretical grounds and collects data that will empirically confirm or reject the predicted relation – the hypotheses (Frankfort-Nachmias et al., 2015: 134). Consequently, if the anticipated relationships are found, the instrument is considered valid.

Construct validity was investigated in the research study to evaluate the validity that is unique to SEM. The construct validity of the measuring scales for the particular sample was confirmed by calculating the average variance extracted (AVE) and composite reliability and by applying the stringent assessment of the observed variables of Henseler, Ringler and Sarstedt (2015: 121) by means of the heterotrait-monotrait (HTMT) criterion.

Information on these measures and the threshold applied in the research study is provided in Table 5.14, followed by a brief description of the process.

Table 5.14: Construct validity applied in the research study

Indicator	Description	Threshold applied
Convergent validity is the degree to which the scale positively correlates with other measures of the same construct (Malhotra, 2019: 279). Convergent validity reflects the extent to which an item shows a positive association with other items of the same construct (Vellnagel, 2019: 83).		
Average variance extracted (AVE)	The AVE is the amount of variance in the observed variables that is explained by the latent construct. AVE is a measure to assess the proportion of variance explained by a construct relative to the variance attributed to measurement error (Malhotra, 2019: 676).	≥ 0.50 (Malhotra, 2019: 676)
Composite reliability	Composite reliability, a measure of internal consistency in scale items, is an indicator of the shared variance among the observed variables used as an indicator of a latent construct (Fornell & Larcker, 1981: 46).	≥ 0.70, but values between 0.60 and 0.70 are acceptable (Hair, Ringle & Sarstedt, 2011: 140; Hamid, Sami & Sidek, 2017: 2; Lin, Huang, Othman & Luo, 2020: 3)

Indicator	Description	Threshold applied
Discriminant validity refers to the extent to which a measure does not correlate with other constructs from which it is supposed to differ (Malhotra, 2019: 279). Discriminant validity explores whether measures that are intended to be different are in fact different and do not relate to one another (Saunders, Lewis & Thornhill, 2016: 451; Van Niekerk, 2020: 264).		
Heterotrait-monotrait (HTMT) criterion	The HTMT criterion assesses the average correlations between indicators across constructs that measure different phenomena, compared to the average correlations between indicators within the same construct (Henseler et al., 2015: 121).	Strict threshold: ≤ 0.85 Liberal threshold: ≤ 0.90 (Henseler et al., 2015: 121).

Source: Author's own compilation

High intercorrelations between variables intended to measure the same concept indicate convergent validity, whereas low intercorrelations between a group of variables intended to measure several constructs support discriminant validity (Kirsten, 2019: 665). Since the former indicates high correlations between theoretically similar conceptions and the latter low correlations with theoretically divergent constructs, convergent and discriminant validity may thus be seen as having opposite qualities (Kirsten, 2019: 665). Convergent validity was assessed by calculating the AVE and composite reliability. Where AVE was greater than the construct's correlation with other constructs (AVE ≥ 0.50), convergent validity was considered to be confirmed. Furthermore, the composite reliability was accepted if the value exceeded the recommended threshold of ≥ 0.70 (Hair et al., 2011: 140; Hamid et al., 2017: 2; Lin et al., 2020: 3). A high alpha value over several observed variables could, however, indicate that the items representing each observed construct are interchangeable and can be argued to correlate with each other. High composite reliability scores across all observed variables can therefore be an indication of a lack of discriminant validity.

To evaluate discriminant validity, Henseler et al.'s stringent assessment of the observed variables (2015: 121) was assessed by means of the HTMT criterion. The HTMT criterion compares the average correlations of indicators across different constructs measuring distinct phenomena with the average correlations of indicators within the same construct (Henseler et al., 2015: 121). This criterion suggests that all variables are distinctively different at a threshold of below 0.85 for strict and 0.90 for liberal discriminant validity. For the purpose of the research study, a strict discriminant validity threshold was desired (≤ 0.85).

The results of the reliability and validity assessment of the measurement model are reported in Chapter 6, section 6.4.1.2 and the revised measurement model in Chapter 6, section 6.4.2.2.

5.2.7.3 Stage 3: Inferential and multivariate analysis

Stage 3 of statistical processing involved inferential and multivariate analysis, as shown in Figure 5.7. Inferential and multivariate statistics allow the researcher to draw conclusions about the population from which the data were collected. Inferential analyses are generally used to determine whether an expected pattern designed by the theory and propositions is found in the observation (Frankfort-Nachmias et al., 2015: 304). Most of the major inferential statistics come from a general family of statistical models known as the General Linear Model and include the *t*-test, analysis of variance (ANOVA), analysis of covariance (ANCOVA), regression analysis and multivariate methods, such as factor analysis, cluster analysis and discriminant function analysis, to name but a few (Trochim, 2021).

For the purpose of the research study, inferential analysis involved four statistical methods. First, correlation analysis was conducted to test the strength and direction of the relationship between the independent and dependent variables (see Chapter 6, section 6.6.1). Second, SEM was conducted to evaluate the relationship between the empirically manifested variables to construct a statistically significant structural model for behavioural intention to continue using same-day delivery apps (see Chapter 6, section 6.6.2). The third step entailed moderation analysis, to assess whether the interaction effects between the variables were conditional upon their disposition in terms of their generational cohort and gender (see Chapter 6, section 6.6.3). Lastly, tests for significant mean differences (specifically independent sample *t*-tests) were conducted to determine whether consumers from various demographic groups (generational cohorts and gender) differed significantly regarding the variables (see Chapter 6, section 6.6.4). The inferential statistics were relied upon to test the research hypotheses (see Chapter 6, section 6.6.2.2), derived from the hypotheses stated and provided in Table 5.1.

Each of the inferential and multivariate statistical procedures applied in the research study is discussed in the following sections.

5.2.7.3.1 Correlation analysis

Correlation analysis is a statistical method used to measure the nature (strength/magnitude and/or direction) of the relationship between two or more variables (Frankford-Nachmias et al., 2015: 338; Venter & Van Zyl, 2017: 173). It is commonly used in academic research to explore the association between different variables and to identify patterns and trends. In correlation analysis, researchers examine the extent to which two variables change together. However, it is important

to note that correlation does not necessarily imply causation. Further research and statistical analyses are required to establish a causal relationship between variables.

Correlation analysis was conducted to examine the direction and magnitude between the measurement model's independent and dependent variables, as manifested in a sample of South African consumers (empirical research objective 4). Pearson's product-moment correlation coefficient (symbolised as *r*) was assessed in the research study to establish the strength and direction of association between two continuous metrics (interval or ratio scaled) variables. The Pearson product-moment correlation coefficient (*r*) represents the linear association between two metric variables and has served as the basis for many multivariate calculations (Kirsten, 2019: 672). A correlation coefficient, ranging from -1 to +1, was calculated to represent the strength and direction of the relationship. A coefficient of +1 indicates a perfect positive correlation, meaning that as one variable increases, the other variable also increases. A coefficient of -1 indicates a perfect negative correlation, meaning that as one variable increases, the other variable decreases. A coefficient of 0 indicates no correlation between the variables (Venter & Van Zyl, 2017: 173).

The associations detected by Pearson's product-moment correlation coefficient are reported in Chapter 6, section 6.6.1, and graphically represented with the aid of scatterplots.

5.2.7.3.2 Structural equation modelling (SEM)

The next stage of the inferential and multivariate statistical analysis procedure involved SEM – a theory-driven approach which combines regression and factor analysis for estimating a series of dependent relationships among a set of constructs represented by multiple measured variables and incorporated into a unified model (Malhotra, 2019: 666; Potgieter, 2012: 224). SEM is therefore a confirmatory statistical method that evaluates a model developed through theory against the data gathered (Van Niekerk, 2020: 228). In a single model, SEM simultaneously evaluates all hypothesised relationships between the variables. For the purpose of the research study, SEM was conducted to evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model (empirical research objective 5).

SEM entails the evaluation of two models, namely a measurement model and a structural (path) model. A measurement model is a key component of SEM used to represent the relationships between latent variables and their observed indicators. It is a statistical model that describes the measurement properties of a set of observed variables (indicators) that are assumed to measure one or more underlying constructs (latent variables) (Brown, 2015: 23; Hair et al., 2014a: 19; Kline,

2016: 339; Van Niekerk, 2020: 256). In SEM, the measurement model specifies how the latent variables are measured by their corresponding observed variables (Brown, 2015: 23; Hair et al., 2014a: 19; Kline, 2016: 339). The measurement model consists of two parts: (1) the factor loadings, which represent the strength of the relationship between the latent variables and their indicators; and (2) the measurement error terms, which represent the variability in the observed variables that are not accounted for by the latent variables (Byrne, 2016: 12; Hair et al., 2014a: 19). The measurement model also allows for the examination of the reliability and validity of the indicators (Byrne, 2016: 12), as discussed above. Without a well-specified measurement model, it is difficult to draw accurate inferences about the relationships between latent constructs and other variables in the model.

A structural model, on the other hand, refers to the part of the model that represents the relationships among latent variables (unobserved constructs) and observed variables (measured indicators). According to Byrne (2016: 50), "… the structural model specifies the causal relationships among the latent variables, and between the latent variables and the observed indicators". It specifies the directional paths and strength of influence among the latent and observed variables in the model. The structural model can be used to test theoretical hypotheses, assess the fit of the model to the data and estimate the strength and direction of relationships among the variables. The structural model is often depicted using path diagrams, which illustrate the hypothesised relationships between the variables (Kline, 2016: 341).

The structural model was assessed by using various statistical measures, including parameter estimates, squared multiple correlations, standardised coefficients, *t*-statistics and *p*-values:

- Parameter estimates represent the strength and direction of the hypothesised relationships between the variables in the model, and they are usually presented in a path diagram. Positive parameter estimates suggest a positive relationship, and negative estimates suggest a negative relationship. The strength of the relationship is indicated by the size of the estimate (Kline, 2016: 129).
- Squared multiple correlation (R^2) is a statistical measure that represents the percentage of the variance in a dependent variable that is explained by an independent variable. It ranges from 0 to 1 and represents the proportion of variance in the observed data that can be explained by the model. A higher R^2 value indicates a better fit between the observed data and the model (Fernando, 2021).

- Standardised coefficients (β) are used to estimate the strength and direction of the relationships between variables while adjusting for the scale of the variables. Larger standardised coefficients indicate stronger relationships between variables, but they only represent direct effects and do not capture indirect effects (Hair et al., 2014a: 210).
- *t*-statistics are used to test the statistical significance of the parameter estimates (Hoyle, 2023: 119). The *t*-value indicates the number of standard deviations the estimate is from zero. A *t*-value greater than 1.96 (assuming a 5% level of significance) suggests that the estimate is statistically significant.
- *p*-values indicate the probability of obtaining a *t*-value as extreme as the one observed, assuming the null hypothesis is true (Kline, 2016: 274). A *p*-value less than 0.05 (assuming a 5% level of significance) suggests that the estimate is statistically significant.

The structural model is presented in Chapter 6, section 6.6.2.

5.2.7.3.3 Moderation analysis

Next, moderation analysis was conducted on the structural model to assess whether the interaction effects between the independent variables on the dependent variable were conditional upon their disposition in terms of generational cohort and gender (moderators) (empirical research objective 6).

Moderation analysis is a statistical method used to examine how the relationship between two variables changes depending on the level of a third variable, called the moderator. In other words, moderation analysis explores whether the nature (strength and/or direction) of the relationship between a predictor variable (X) and a dependent variable (Y) is affected by the value of a third variable (W) (Statistics Solutions, 2018). The causal effect of the independent variable (X) on the dependent variable (Y) is denoted as *c* (see Figure 5.8 below). This effect is dependent on the value or level of the moderating variable (W) (Kirsten, 2019: 686). Consequently, moderation analysis is aimed at establishing under what circumstances, for whom and/or to what extent a causal effect between an independent (X) and dependent (Y) variable exists.

Figure 5.8 illustrates the moderation effect using a path diagram.

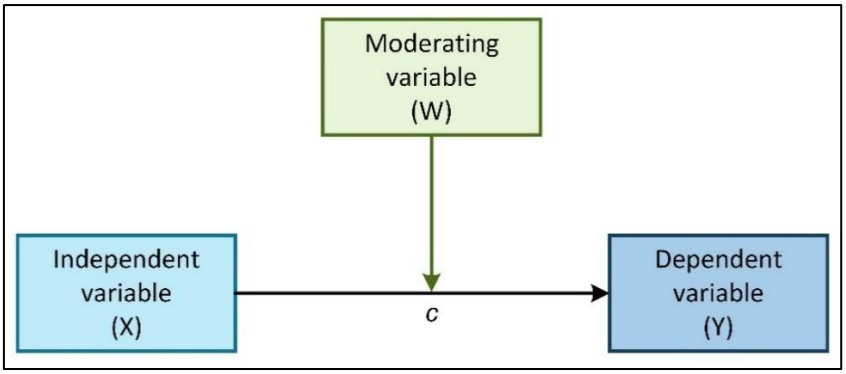

Figure 5.8: Path diagram illustrating a simple moderation model
Source: Kirsten (2019: 686)

To perform moderation analysis, a regression model is typically used that includes interaction terms between the predictor variable and the moderator variable. The interaction term estimates the effect of the moderator on the relationship between the predictor and dependent variable. The significance of the interaction term indicates whether the moderator has a significant impact on the relationship between X and Y.

Regression-based moderation analysis was conducted in the research study to examine (1) the interaction effects between the independent variables and dependent variable, and consumers' disposition in terms of *gender* and (2) the interaction effects between the independent variables and dependent variable, and consumers' disposition in terms of the *generational cohort (age group)*. A three-step process was followed in the research study. First, the initial, unmoderated, equation representing the extent to which the dependent variable (Y) is predicted by the independent variable (X) was estimated. Second, the determination of the moderated relationship was assessed by considering the change in the squared multiple correlations (R^2). The existence of a significant moderating effect would be confirmed if the R^2 change was statistically significant ($p \leq 0.05$), considering the regression coefficient (XW). Third, any significant moderation effects identified in the analyses were probed using Johnson-Neyman intervals and a simple slope analysis. Johnson-Neyman intervals are a statistical tool used in moderation analysis to identify regions of significance in the interaction between two variables (Hayes, 2018: 253). Simple slope analysis is used to explore how the relationship between two variables changes at different levels of a third variable (moderator). It examines the slope of the regression line between the predictor and outcome variable at different levels of the moderator (Hayes, 2018: 249).

The aim of the moderation analysis was to determine whether the significant pathways that were detected in the SEM were conditional upon gender and generational cohort. The results of the moderation analysis are reported in Chapter 6, section 6.6.3.

5.2.7.3.4 Test for group mean differences

Test for significant group means differences were examined to determine whether consumers from various demographic groups (generational cohort and gender) differ significantly regarding the independent variables and dependent variable (empirical research objective 7).

For the purpose of the research study, independent sample *t*-tests were used to establish whether there were any statistically significant differences in mean scores between two categories or independent groups and one continuous variable (Wiid & Diggines, 2021: 323). Levene's test for equality of variances was first applied to determine whether equal variances could be assumed in the data. This is a statistical test used to assess whether the variances of two or more groups are equal or not and is commonly used to determine the assumption of homogeneity of variances in independent *t*-tests. Thereafter, the level of significance was determined by assessing the *p*-value. A *p*-value of 0.05 is generally considered significant, indicating a 95% level of confidence that the observed results are not due to chance and are likely representative of the true population expectation for a given test (Du Plessis, 2018: 215). Cohen's *d* (1988), a statistical measure of effect size that is used to quantify the difference between the means of two groups, was applied to interpret any statistically significant differences detected in the data.

Table 5.15 summarises the empirical research objectives of the study and the statistical methods or techniques employed to reach the specific objective.

Table 5.15: Empirical research objectives and statistical methods employed

Empirical research objective	Statistical methods
RO1: To explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market.	Univariate descriptive statistics (mean, standard deviation, skewness and kurtosis) *[Refer to Chapter 6, sections 6.2, 6.3 and 6.5]*
RO2: To explore the suitability of the individual items measuring the latent constructs in the research instrument for a sample of South African consumers.	
RO3: To assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention.	Confirmatory factor analysis (CFA) (model fit, reliability and validity) *[Refer to Chapter 6, section 6.4]*

Empirical research objective	Statistical methods
RO4: To examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers.	Correlation analysis *[Refer to Chapter 6, section 6.6.1]*
RO5: To evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model.	Structural equation modelling (SEM) *[Refer to Chapter 6, section 6.6.2]*
RO6: To empirically assess the interaction effects between the independent variables and the dependent variable, and two demographic conditions (moderators), namely generational cohort and gender.	Moderation analysis *[Refer to Chapter 6, section 6.6.3]*
RO7: To assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps.	Test for group mean differences *[Refer to Chapter 6, section 6.6.4]*
RO8: To formulate conclusions and make recommendations for the marketing and retailing industry, and for possible future research, based on the results of the research study.	Addressed in Chapter 7

Source: Author's own compilation

Step 8, the last step in the research process as illustrated in Figure 5.1, involved writing the report, interpreting the analysed data, making inferences and achieving the empirical objectives of the research study. In Chapter 7 of the research report, research conclusions, limitations and recommendations are formulated. Step 8 concludes the research project and will be presented in Chapter 7 of this research study.

5.3 ETHICAL CONSIDERATIONS AND PRINCIPLES

Ethics in research, according to Saunders et al. (2019: 252), denotes the standards of behaviour that guide empirical conduct in relation to the respondents who are affected by it in some way. Researchers should be mindful of their responsibility to act morally and be aware of ethical reasoning (Du Plessis, 2018: 218).

Ethical clearance was obtained from the Department of Marketing and Retail Management's Ethics Review Committee (ERC Reference # 2020_MRM_002) to conduct the research study and to distribute the web-based self-administered questionnaire to the target population identified in section 5.2.5. Refer to Annexure B for the ethics clearance certificate. The research study followed the complete application process, and data collection began after obtaining approval from the Ethics Review Committee.

Appropriate ethical principles were applied throughout the research study. The ethical principles and rationale for each principle are briefly discussed below (Saunders et al., 2019: 157-159):

- *Integrity, fairness and open-mindedness of the researcher.* The quality of the research study partly rests on the integrity, fairness and open-mindedness of the researcher. Researchers must be truthful, impartial and transparent and promote correctness, thereby avoiding dishonesty, misinterpretation, prejudice, reckless commitments or deceitful promises. Researchers should furthermore declare any conflict of interest or commercial association where applicable. To maintain the integrity of the research study, the researcher remained unbiased, truthful and transparent throughout the research study by openly communicating the nature of the research study, the purpose of collecting data and respondents' rights in terms of voluntariness of participation and freedom to withdraw. The researcher communicated all required information in the informed consent (or cover letter) and refrained from withholding any important information from the respondents. The cover letter can be found in Annexure D.

- *Respect for others.* Respect for others focuses mainly on ensuring participants' right to independence and autonomy in the research process (Hefer, 2017:153). Conducting research entails social responsibility and obligations to the respondents and those affected by the study in some way. The rights of individuals should therefore be recognised and their dignity respected. Potential respondents were invited to participate in the research study, voluntary participation was stipulated in the cover letter (Annexure D), respondents' freedom to withdraw without any consequences was highlighted and no personal and identifiable information was obtained from respondents.

- *Non-maleficence.* Non-maleficence is the principle dictating that harm should not come to individuals because they participated in a research study (Gelling, 2015). Harm may occur through risks of emotional well-being, mental or physical health, or social or group cohesion and may take on several forms, such as embarrassment, stress, discomfort, pain or conflict. No foreseeable risk of harm or side effects to the prospective respondents was envisioned. Respondents might have incurred some financial costs in terms of data costs to complete the online survey, but such costs were minimal.

- *Justice.* Justice refers to the distribution of risk to society, implying that the selection of prospective respondents should not be biased in terms of classes or types of individuals (Hefer, 2017: 154). Prospective respondents were conveniently selected as discussed in section 5.2.5.1, and the data collection process was managed by an independent data collection company (Springvale Online).

- *Voluntariness and right to withdrawal.* As previously mentioned, the right not to participate in a research study is absolute. Likewise, individuals have the right not to be beleaguered to participate and respondents have the right to withdraw from participating in the research study at any time without any consequences. Potential respondents' rights in terms of voluntariness and their right to withdraw were clearly communicated in the cover letter (see Annexure D). Respondents could furthermore refrain from completing the online questionnaire, should they so wish, without any consequences.
- *Privacy of participants.* Privacy is a key principle that underpins several other principles – respect for others, avoidance of harm, voluntariness of participation, informed consent, confidentiality, anonymity, responsibility and compliance with data management. In this study, the privacy of respondents was ensured by using a data collection company (Springvale Online), and therefore the researcher had no contact or personal details of the potential respondents. No personal or identifiable information was gathered from participants and therefore there was no way of linking the respondent to the survey.
- *Confidentiality of data and anonymity of participants.* The purpose of research studies is to answer 'who', 'what', 'when', 'where', 'how' and 'why', and not to focus on those who provide the answers specifically. Research instruments should therefore be developed to be non-attributable unless a specific identifiable attribute is required and justified. The reliability of data is also likely to be enhanced when confidentiality and anonymity are assured. The research instrument that was employed in the research study was developed to be anonymous and the researcher had no way of connecting the information provided to the respondent personally. Data collection was administered by an independent data collection company and no personal identifiers of respondents were known to the researcher or statistician.
- *Responsibility in the analysis of data and reporting of the findings.* Care should be taken to ensure that the results are reported accurately and are a true reflection of the data obtained, without falsifying or adapting the results, irrespective of whether the results contradict the expected outcomes. The researcher worked with a statistician to ensure that the data were properly analysed and the results were reported copiously and accurately and were therefore a true reflection of the data collected for the research study.

The above ethical principles were adhered to throughout the research study to ensure the integrity of the study and reliability of the data collection process. Consumers were invited to participate in the research study through an e-mail that provided detailed information about the study's purpose, the nature of their participation, the benefits and potential risks involved, as well as the assurance

of confidentiality and anonymity. Anonymity was maintained by not collecting any personally identifiable information from respondents. Confidentiality was emphasised, with the explanation that the data would be used solely for academic purposes. The cover letter included an informed consent agreement, stating that respondents' completion and submission of the online survey indicated their agreement to use the results for research purposes only (refer to Annexure D). The researcher is furthermore responsible for how the data were analysed and reported, as well as for protecting the confidentiality and security of the information obtained.

5.4 CONCLUSION

Chapter 5 provided a detailed description of the research methodology that was applied in determining the factors that influence consumers' behavioural intention to continue using same-day delivery apps in South Africa.

The steps in the research methodology process were outlined in a discussion of the research paradigm and approach adopted by the researcher, the research design, the target population and sampling strategies, the instrument development process, the data collection strategies and techniques, as well as the statistical techniques used to analyse the collected data. The chapter concluded with a discussion of the ethical considerations and principles that were adhered to throughout the research study.

CHAPTER 6:
RESEARCH FINDINGS

6.1 INTRODUCTION

Chapter 6 offers a comprehensive presentation and interpretation of the research results derived from various statistical analyses conducted to address the empirical research objectives and evaluate the research hypotheses. The chapter starts with an overview of the profile of respondents who formed part of the research study. Thereafter, the application and reporting of descriptive statistics, correlations as well as inferential and multivariate statistics are applied and reported to achieve the research objectives and assess the stated hypotheses. Chapter 6 concludes with a thorough discussion of the outcomes related to the research hypotheses, and the interpretation of the results in conjunction with pertinent literature from the field. The final step of the empirical research process, which entails discussing and interpreting the results and stating the conclusions, limitations, and recommendations of the study (empirical research objective 8), is reported in Chapter 7.

6.2 PROFILE OF RESPONDENTS

An overview of the composition of respondents who formed part of the research study and consumers' use of same-day delivery apps are discussed in this section.

6.2.1 DEMOGRAPHIC PROFILE OF RESPONDENTS

The research instrument was in the form of a self-administered, web-based questionnaire sent to a diverse group of consumers residing in Gauteng, KwaZulu-Natal and the Western Cape provinces of South Africa, and who (at the time of data collection) used same-day delivery apps. A non-probability convenience sample of 485 usable questionnaires were returned, yielding a response rate of 4.85%. The sample size (n = 485) was considered suitable for achieving adequate statistical results to detect significant statistical properties to perform correlation analyses through group mean differences, regression analysis, SEM and moderation analysis.

The profile of respondents is described according to the following variables: gender, generational cohort, age, residing province and ethnic orientation. A demographic profile is included for non-comparative purposes and merely as an indication of completeness and representativeness.

The composition of the sample (n = 485) is presented in Table 6.1 and discussed thereafter.

Table 6.1: Composition of the sample (n = 485)

	Category	Frequency (n)	Percentage
Gender	Female	337	69.5%
	Male	145	29.9%
	Not specified	3	0.6%
	Other	0	0%
	Total	**485**	**100.0**
Generational cohort	1930–1949 (Silent Generation)	0	0%
	1950–1969 (Baby Boomers)	17	3.9%
	1970–1989 (Generation X)	177	36.5%
	1990–2000 (Generation Y)	263	54.2%
	2001–2003 (Generation Z)	26	5.4%
	Total	**485**	**100%**
Age groups	18–24	101	20.8%
	25–30	161	33.2%
	31–40	144	29.7%
	41+	79	16.3%
	Total	**485**	**100%**
Residing province	Gauteng	291	60%
	KwaZulu-Natal	106	21.9%
	Western Cape	87	17.9%
	Not specified	1	0.2%
	Other	0	0%
	Total	**485**	**100.0**
Ethnic orientation	Black	344	70.9%
	Coloured	56	11.5%
	Indian	22	4.5%
	White	59	12.2%
	Not specified	4	0.8%
	Other	0	0%
	Total	**485**	**100.0**

Table 6.1 indicates that most of the respondents were female (69.5%; n = 337), and only a relatively small percentage comprised male participants (29.9%; n = 145). The unequal distribution of respondents according to gender could be attributed to the fact that, traditionally, women in a household lead all major purchase decisions for their families, especially for food and groceries (Deon, 2011: 5424; Reinartz et al., 2011: 53; Shea & Zivic, 2011: 23). These results are in line with the literature, which affirms that women are more likely to shop online for groceries (Choi, 2013: 16) and are avid mobile grocery app users, as they are typically the main shopper of the household (Martínez & Porter, 2012: 234; Punjnai, 2017: 158). It is therefore plausible that male participants were restricted by the screening questions posed by the research instrument.

Table 6.1 illustrates that 54.2% (n = 263) of the respondents were Generation Y-ers (born between 1990 and 2000), followed by 36.5% (n = 177) of the respondents being Generation X-ers (born between 1970 and 1989). Although the distribution of the different age categories was fairly even, there was a peak at the 25 to 30 (33.2%; n = 161) and 31 to 40 (29.7%; n = 144) age groups. The peak could suggest that respondents comprised working individuals that formed part of a married household generally with one or more children. Overall, the sample consisted predominantly of black respondents (70.9%; n = 344) and participants residing mainly in Gauteng (60%; n = 291). The distribution of demographics among the sample is considered rational as Gauteng is seen as the business hub of South Africa. Also, many of the same-day delivery apps available to the public, at the time of data collection, were offered by selected participating retailers located in Gauteng.

To summarise, the biographical profile of respondents comprised 69.5% (n = 337) females and 29.9% (n = 145) males. Most (62.9%; n = 305) respondents were between the ages of 25 and 40 and the majority of respondents were Generation Y-ers (54.2%; n = 263), followed by Generation X-ers (36.5%; n = 177). Lastly, most (60%; n = 291) respondents resided in Gauteng, followed by KwaZulu-Natal (21.9%; n = 106) and then the Western Cape (17.9%; n = 87). The sample was considered representative of the target population.

Respondents were posed three questions to establish empirical research objective 1, which is presented in the next section, and which aimed to explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market.

6.2.2 RELEVANCE OF SAME-DAY DELIVERY APPS IN THE SOUTH AFRICAN CONSUMER MARKET

To explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market, respondents were asked to indicate how frequently they used certain online technologies or platforms, which specific same-day delivery apps available in the South African market they used to purchase products (at the time of data collection) and how often they used same-day delivery apps for various reasons. The results are reported in the sections that follow.

6.2.2.1 Use of online technologies and/or platforms

Participants were asked to indicate, on a scale of 1 (never) to 5 (always), how frequently they used a selected list of online platforms and/or technologies (question 7 of the questionnaire). Figure 6.1 graphically portrays the distribution of results.

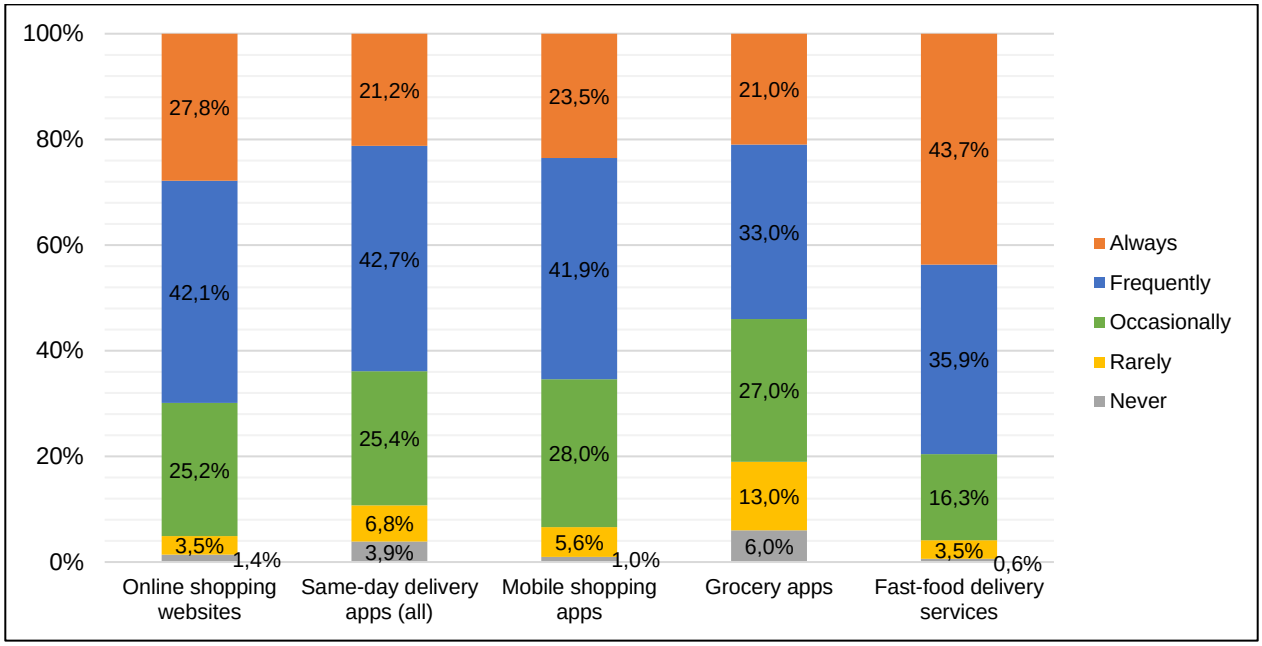

Figure 6.1: Frequency of use of different technologies or online platforms (n = 485)
Source: Author's own compilation

It is evident from Figure 6.1 that all e-commerce platforms were frequently (always and frequently) used by respondents, with fast-food delivery services accounting for 79.6% (n = 386) of respondents' usage, followed by online shopping websites (69.9%; n = 339) and mobile shopping apps (65.4%; n = 317). Grocery apps (54%; n = 262) and same-day delivery apps (63.9%; n = 310) were used less often by respondents, which could be due to the infancy of grocery-related same-day delivery apps in the South African market at the time of data collection. From the above results, it can be inferred that consumers use various online shopping platforms and technologies available in the South African market regularly. It can therefore be presumed that an online presence is meaningful in the South African retailing and restaurant industry.

The frequent use of various e-commerce platforms reported in Figure 6.1 is consistent with FNB's Merchant Services statistics showing that total online sales increased by 55% in 2020 and a further 42% in 2021, which was said to be driven by a rise in less traditional e-commerce industries, such as online platforms (Business Tech, 2022). According to FNB's report, an upsurge in the e-commerce estimated value indicates how the COVID-19 pandemic exponentially accelerated

the use of e-commerce (Business Tech, 2022). Before the COVID-19 pandemic, e-commerce accounted for 8% of total card payments spent in the retail space, whereas at the end of 2021, this figure rose to 14% (Business Tech, 2022). Additionally, online spending on products doubled in 2020, reflecting a 102% increase, which saw a further 39% growth in 2021 (Business Tech, 2022). The South African e-commerce market has grown exponentially and was estimated at approximately R200 billion per annum, which is believed will reach more than R400 billion by 2025 (Business Tech, 2022).

6.2.2.2 Use of available same-day delivery apps

Question 3 of the questionnaire requested participants to select, from a predetermined list of same-day delivery apps available in South Africa, all the apps which they used on a regular (weekly) basis. Table 6.2 lists the various apps participants selected, ranked according to the most used.

Table 6.2: List of same-day delivery apps used by respondents

Same-day delivery app	Frequency (n)	Percentage	Same-day delivery app	Frequency (n)	Percentage
Debonairs Pizza	329	**68.3%**	Ocean Basket	39	8.1%
Mr D Food	298	**61.8%**	Krispy Kreme	18	3.7%
Uber Eats	292	**60.6%**	iStore (same-day delivery option only)	16	3.3%
KFC Delivery	248	51.5%	Zulzi	16	3.3%
Takealot.com (same-day delivery option only)	210	43.6%	The Dog Food App	14	2.9%
Checkers Sixty60	197	40.9%	OneCart	13	2.7%
McDelivery	162	33.6%	OrderIn	12	2.5%
Burger King	134	27.8%	Simply Asia	10	2.1%
Steers	127	26.3%	CartRun	9	1.9%
Dis-Chem DeliverD	113	23.4%	Deliveroo	9	1.9%
Nando's	105	21.8%	Other	9	1.9%
Pick n Pay ASAP!	97	20.1%	Thirst Busters	6	1.2%
Bottles Alcohol Delivery	77	16%	Pekkish SA	5	1%
Fishaways	73	15.1%	Quench	4	0.8%
Woolies Dash	53	11%	Stulo	4	0.8%
Pizza Hut	46	9.5%	Zomato	3	0.6%

As discussed in Chapter 2, section 2.5.2, several on-demand food and grocery delivery apps offer a same-day delivery option. These businesses are classified as either grocery retailers or food outlets/restaurants serving the public directly, or by means of a third-party intermediary app. From the results tabulated in Table 6.2 above, it is apparent that grocery-related same-day delivery apps were not widely used by participants, as the three major same-day delivery apps in the direct

grocery app category in South Africa, namely Checkers Sixty60 (40.9%; n = 195), Pick n Pay ASAP! (20.1%; n = 97) and Woolies Dash (11%; n = 53), were not used by participants regularly. The low penetration rate could be due to the inception of these apps in the South African market, consumers' limited knowledge of these apps, or the limited reach of these types of apps in the market as only certain participating retailers had implemented these apps at the time of data collection.

In the food outlet/restaurant category, however, many participants used direct same-day delivery apps as well as third-party apps – the most used apps being Debonairs Pizza (68.3%; n = 328), Mr D Food (61.8%; n = 297), Uber Eats (60.6%; n = 293), KFC Delivery (51.5%; n = 248) and McDelivery (33.6%; n = 162). Since these apps have been available in the market for many years – for instance, Debonairs Pizza introduced delivery services in 1991, Mr D Food launched in 2014 and Uber Eats launched in 2016 – they have built brand loyalty and equity among numerous satisfied, loyal and returning customers. It is therefore understandable why food delivery apps were used more often by participants. It must be borne in mind, however, that the data were collected during the COVID-19 pandemic and regulations prohibited fast-food outlets and restaurants from offering sit-down services and were furthermore restricted by their operating hours. These regulations meant that many food outlets could only offer delivery services; hence the potential increase in the use of food delivery services and related mobile apps that can be seen from the results in Table 6.2.

A comprehensive summary indicating the use of various platforms and technologies according to the demographic profile of the participants can be found in Annexure F.

6.2.2.3 Reasons for using same-day delivery apps

Question 4 of the questionnaire attempted to explore the reasons why consumers use same-day delivery apps. Respondents were requested to indicate, on a scale ranging from never (1) to always (5), how often they used same-day delivery apps for various reasons. Table 6.3 tabulates these results according to importance.

Table 6.3: Reasons for using same-day delivery apps (n = 482)

Reason(s)	Never	Rarely	Occasionally	Frequently	Always
I use same-day delivery apps …					
because it is convenient to have products delivered to my door.	0.4%	2.5%	17.2%	26.8%	**53.1%**
because it is safer than having to physically go to the store.	1.2%	4.6%	18%	24.9%	**51.2%**
to maintain social distancing because of the COVID-19 pandemic.	1.9%	3.9%	17%	29.7%	**47.5%**
to browse for specials, deals or discounts.	2.5%	4.8%	14.5%	37.8%	40.5%
to avoid having to physically go to a store.	1%	4.4%	24.3%	30.5%	39.8%
to find a store closest to me.	2.5%	6.4%	22%	30.1%	39%
to check product availability.	2.5%	6.2%	19.3%	33.2%	38.8%
to compare prices.	4.4%	8.9%	18.9%	30.3%	37.6%
to compare products.	5%	8.3%	22.4%	28%	36.3%
to benefit from online-only deals or specials.	1.9%	7.3%	24.1%	31.7%	35.1%
to compare services.	6%	12.9%	25.1%	23.9%	32.2%
to read reviews.	8.3%	13.9%	22.4%	26.8%	28.6%
to share product details with others (such as peers, friends or family members).	7.3%	14.5%	24.7%	25.5%	28%
to find the contact details of a specific retailer.	7.5%	15.1%	26.6%	24.9%	25.9%
to collect or use coupons or vouchers.	5.6%	15.1%	26.3%	27.6%	25.3%
to purchase products.	1%	3.5%	31.7%	40.7%	23%
to give reviews.	8.7%	21.2%	27.8%	21%	21.4%
to acquire services.	5%	14.1%	32.4%	33.2%	15.4%

As is evident from Table 6.3, the respondents who indicated that they always used same-day delivery apps had specific reasons for this, namely it was convenient to have products delivered to their door (53.1%; n = 256), it was safer than having to physically go to the store (51.2%; n = 247) and to maintain social distancing during the COVID-19 pandemic (47.5%; n = 229). Participants were furthermore less likely to use same-day delivery apps to collect or use coupons (20.7%; n = 100), share product details with others (21.8%; n = 105), find contact details of a specific retailer (22.6%; n = 109), give reviews (29.9%; n = 144) and read reviews (22.2%; n = 107).

It must be borne in mind that, at the time of data collection, South Africa experienced social distancing and national lockdown regulations issued by the Minister in terms of the State of Disaster Management Act: COVID-19. Furthermore, civil unrest and violent protest action were imminent in large parts of the surveyed provinces because of the imprisonment of former President Jacob Zuma for contempt of court (The Presidency, 2021). It can be expected that the restrictions and regulations enforced due to the COVID-19 pandemic, as well as the violent protests and riots, had an impact on respondents' inclination to use same-day delivery apps for personal and physical safety reasons. These statistics are, however, consistent with the findings reported in Deloitte's

consumer insights report, stating that consumers prefer online shopping because it is more convenient, it saves time and because of the COVID-19 pandemic (Deloitte, 2021: 6). It is evident from these results that consumers use same-day delivery apps mainly for their convenience and not necessarily because of the augmented and auxiliary services offered by same-day delivery apps, such as contact information, reviews, coupons and special offerings.

A comprehensive summary indicating the reasons why respondents used same-day delivery apps, according to the demographic profile of the respondents, can be found in Annexure G.

The preceding section provided supporting evidence for empirical research objective 1, which aimed to explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market. From these results, it can be inferred that same-day delivery apps have value in the South African consumer market and that retailers could benefit from adopting a same-day delivery business model to reach the wider South African market.

The following section deals with the descriptive statistics to gain an initial impression of the characteristics of the data collected.

6.3 DESCRIPTIVE STATISTICS: MEANS AND STANDARD DEVIATION OF THE LATENT VARIABLES

As discussed in Chapter 5, section 5.2.7.1, descriptive statistical analysis is used to draw comparisons and create descriptions for different variables, numerically. In this section, the descriptive statistics for the dataset are explored and discussed to establish the suitability of the individual items measuring the latent variables in the research instrument involving a sample of South African consumers (empirical research objective 2). The descriptive results reported in the sections below were derived from Section B (question 5) and Section C (question 6) of the research instrument, measuring the factors that influence behavioural intention and use behaviour. In questions 5 and 6, participants were required to indicate the extent to which they disagreed (1) or agreed (5) with a list of 70 statements relating to same-day delivery apps.

The section commences with an overview of the means and standard deviations for each of the observed constructs presented in the theoretically derived conceptual model (see Figure 4.1). The section then follows with a discussion of the skewness and kurtosis observed in the dataset, to assess the assumption of normality.

6.3.1 REPORTING OF MEANS AND STANDARD DEVIATIONS OF THE LATENT VARIABLES IN THE RESEARCH INSTRUMENT

The mean ($\bar{x}$) and standard deviation (s) values for the measuring instrument were calculated and are reported below. The mean is a measure of central tendency which denotes the value between several different elements (Malhotra, 2019: 443; Neuman, 2014: 399; Salkind, 2018: 134). The standard deviation is a measure of variability and refers to the average distance of the values in their distribution from the mean (Neuman, 2014: 401; Van Niekerk, 2020: 241). The mean and standard deviation scores for each of the items used to measure the 12 constructs in the research instrument (11 independent constructs and 1 dependent construct), as well as the overall values per construct are explored and interpreted below.

The scale items were measured on a 5-point Likert scale where 1 = strongly disagree and 5 = strongly agree, over a midpoint of 3 (neither disagree nor agree). To assist in the interpretation of the mean scores, the following classifications were used: 1 to 1.50 implied that respondents strongly disagreed; 1.51 to 2.50 inferred that respondents disagreed; 2.51 to 3.50 indicated that respondents were unsure or felt impartial; 3.51 to 4.50 implied that respondents agreed; above 4.50 indicated that respondents strongly agreed. Furthermore, a standard deviation of ≥ 1 was considered a significant dispersion of responses in the dataset.

It is important to note that these descriptive statistics report on the scale items in isolation and do not infer any direction or relationship regarding the dependent variable.

6.3.1.1 Performance expectancy

The mean, ranked according to the highest mean score, and the standard deviation values for each of the six items used to measure performance expectancy are shown in Table 6.4. Items 5.9, 5.22, 5.42, 5.50, 5.55 and 5.59 of the research instrument measured the performance expectancy construct.

Table 6.4: Performance expectancy: Mean and standard deviation scores

Item	Item mean	Item std dev.
[PE6] I can save time when I use same-day delivery apps to purchase products.	4.42	0.646
[PE1] Using same-day delivery apps frees up time, allowing me to do something else, and therefore increases my productivity.	4.35	0.772
[PE5] I find same-day delivery apps useful in my daily life.	4.33	0.677

Item	Item mean	Item std dev.
[PE2] Using same-day delivery apps help me accomplish my shopping goals faster.	4.32	0.781
[PE3] Using same-day delivery apps allow me to achieve things that are important to me while I wait for products to be delivered.	4.28	0.784
[PE4] Same-day delivery apps are beneficial to me.	4.25	0.692

Across all items, the average mean score was 4.32, which suggests that respondents generally agreed with these items that related to performance expectancy. The highest level of agreement was with item PE6 with a mean score of 4.42 (*s* = 0.646) ("*I can save time when I use same-day delivery apps to purchase products*"). Although still in agreement, the lowest level of agreement was with item PE4 with a mean score of 4.25 (*s* = 0.692) ("*Same-day delivery apps are beneficial to me*"). The high mean scores across all statements indicate that respondents felt that using same-day delivery apps could save them time to purchase products and services and free up their time, thus increasing their productivity. It can be assumed that consumers will use same-day delivery apps if they feel that the same-day delivery app will provide them with the benefits of performing specific activities in everyday situations.

6.3.1.2 Effort expectancy

Table 6.5 details the mean and standard deviation scores of the five items (items 5.7, 5.16, 5.29, 5.36 and 5.46) that relate to the effort expectancy construct. The responses were ranked according to the highest mean score.

Table 6.5: Effort expectancy: Mean and standard deviation scores

Item	Item mean	Item std dev.
[EE3] I find same-day delivery apps easy to use.	4.46	0.631
[EE1] Learning how to use same-day delivery apps is easy for me.	4.45	0.689
[EE4] The way I interact with same-day delivery apps is clear and understandable.	4.31	0.727
[EE2] It is easy for me to become skilful in using same-day delivery apps.	4.29	0.676
[EE5] Same-day delivery apps require minimal effort from me.	4.23	0.819

Across all items which related to effort expectancy, the average mean score was 4.38, indicating that respondents generally agreed with the statements regarding effort expectancy. The highest level of agreement was with item EE3 ("*I find same-day delivery apps easy to use*"), with a mean score of 4.46 (*s* = 0.631), as well as item EE1 ("*Learning how to use same-day delivery apps is easy for me*"), with a mean score of 4.45 (*s* = 0.689). The high scores are an indication that respondents considered same-day delivery apps easy to learn and user-friendly. These results

are in line with Venkatesh et al.'s conceptualisation (2012: 159) of the effort expectancy construct. Accordingly, respondents generally agreed that it would be easy for them to use and learn how to use same-day delivery apps.

6.3.1.3 Facilitating conditions

The mean and standard deviation scores for each of the five items used to measure facilitating conditions are presented in Table 6.6. The responses were ranked according to the highest mean score. The facilitating conditions construct was measured through items 5.13, 5.21, 5.23, 5.47 and 5.63 of the research instrument.

Table 6.6: Facilitating conditions: Mean and standard deviation scores

Item	Item mean	Item std dev.
[FC3] I have the knowledge necessary to use same-day delivery apps.	4.43	0.648
[FC4] I have the resources necessary to use same-day delivery apps.	4.35	0.775
[FC5] I feel comfortable using same-day delivery apps.	4.32	0.678
[FC2] Same-day delivery apps are compatible with other technologies I use.	4.18	0.755
[FC1] I can get help from others when I have difficulties using same-day delivery apps.	3.95	0.901

The average mean score for all questions relating to facilitating conditions was 4.25, indicating that respondents largely agreed with these statements. The highest level of agreement was with item FC3 with a mean score of 4.43 (s = 0.648) ("*I have the knowledge necessary to use same-day delivery apps*"), followed by item FC4 with a mean score of 4.35 (s = 0.775) ("*I have the resources necessary to use same-day delivery apps*"). The lowest level of agreement was with item FC1 with a mean score of 3.95 (s = 0.901) ("*I can get help from others when I have difficulty using same-day delivery apps*"), indicating that respondents would rather become acquainted with same-day delivery apps on their own than obtain help from others.

The overall agreement with the statements related to facilitating conditions indicates that respondents were well equipped and had the necessary resources to successfully use same-day delivery apps without the help of others. These results are understandable as the sample comprised consumers who used same-day delivery apps (100%; n = 485) and therefore had the necessary resources, such as stable Internet connectivity and/or mobile data and a smartphone, as well as adequate knowledge of technology and mobile shopping apps in general.

6.3.1.4 Social influence

Table 6.7 details the mean and standard deviation scores for each of the six scale items relating to the social influence construct. The responses were ranked according to the highest mean score. Scale items 5.3, 5.12, 5.26, 5.32, 5.38 and 5.54 of the research instrument were used to measure the social influence construct.

Table 6.7: Social influence: Mean and standard deviation scores

Item	Item mean	Item std dev.
[SI2] People whose opinions I value use same-day delivery apps.	3.89	0.924
[SI1] People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps.	3.86	1.000
[SI6] Mass media (such as TV, radio, magazines and social media) influence my decision to use same-day delivery apps.	3.73	1.077
[SI3] People who influence my behaviour think that I should use same-day delivery apps.	3.73	1.029
[SI4] Friends' suggestions and recommendations affect my decision to use same-day delivery apps.	3.46	1.165
[SI5] Family members influence my decision to use same-day delivery apps.	3.45	1.137

The average mean score for all items relating to social influence was 3.69, indicating that respondents generally agreed with the statements about social influence. The highest level of agreement was with item SI2 with a mean score of 3.89 (s = 0.924) ("*People whose opinions I value use same-day delivery apps*"), closely followed by item SI1 with a mean score of 3.86 (s = 1.000) ("*People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps*"). Based on these statistics, it can be presumed that respondents agreed that their decisions were slightly influenced and shaped by the suggestions, comments, reviews and posts of significant others and other users. Furthermore, respondents were somewhat impartial towards items SI4 ($\bar{x}$ = 3.46; s = 1.165) and SI5 ($\bar{x}$ = 3.45; s = 1.137) concerning the influence friends and family exerted on their decision to use same-day delivery apps. From the slightly impartial response recorded, it can be assumed that respondents were not likely influenced by their interpersonal influencers, such as friends and family as suggested by literature (e.g. Chopdar et al., 2018: 113; Hew et al., 2015: 1273; Malik et al., 2017: 109).

The overall standard deviation for the social influence construct was slightly higher with a variation of 1.055, with the most variance from items SI4 (s = 1.165) and SI5 (s = 1.137). Both items measured the influence friends and family had on participants' inclination to use same-day delivery apps. The high standard deviation is indicative of variability in the data, which could be attributed to demographic differences as women tend to be more sensitive to others' opinions and prefer

social interactions when forming intentions to use new technology (Lee et al., 2017: 566; Venkatesh et al., 2003: 453). The literature also suggests that older individuals are more likely to rely on their social support structure when they have less experience with technology (Onwona-Agyman, 2019: 7).

6.3.1.5 Hedonic motivation

The mean and standard deviation scores for the five scale items (items 5.6, 5.20, 5.34, 5.45 and 5.56) related to the hedonic motivation construct are tabulated in Table 6.8. The responses were ranked according to the highest mean score.

Table 6.8: Hedonic motivation: Mean and standard deviation scores

Item	Item mean	Item std dev.
[HM4] Using same-day delivery apps is interesting.	4.28	0.722
[HM1] Using same-day delivery apps is fun.	4.16	0.763
[HM2] Using same-day delivery apps is enjoyable.	4.15	0.798
[HM5] I experience pleasure when using same-day delivery apps.	4.09	0.802
[HM3] Using same-day delivery apps is very entertaining.	3.96	0.896

The average mean score for all items relating to hedonic motivation was 4.13, indicating that respondents largely agreed with the statements. The highest level of agreement was with item HM4 with a mean score of 4.28 (s = 0.722) ("*Using same-day delivery apps is interesting*"), followed by items HM1 ($\bar{x}$ = 4.16; s = 0.763) and HM2 ($\bar{x}$ = 4.15; s = 0.798) ("*Using same-day delivery apps is fun"*), indicating that respondents found it gratifying to use same-day delivery apps.

From the general agreement with the items relating to hedonic motivation reported in Table 6.8, it can be assumed that the majority of respondents used same-day delivery apps because they were fun, enjoyable and interesting to use and they experienced pleasure when using these apps. These results are consistent with the literature arguing that if a technology is pleasurable to use, individuals can gain enjoyment from it, which will ultimately influence their intention to pursue the technology (Lee, 2009: 852; Mavuya, 2016: 20).

6.3.1.6 Habit

Table 6.9 details the mean and standard deviation scores for each of the four scale items (items 5.2, 5.19, 5.41 and 5.52) related to the habit construct. The responses were ranked according to the highest mean score across the scale items.

Table 6.9: Habit: Mean and standard deviation scores

Item	Item mean	Item std dev.
[HA4] Using same-day delivery apps has become second nature to me.	4.03	0.887
[HA1] The use of same-day delivery apps has become a habit of mine.	4.02	0.966
[HA3] I must use same-day delivery apps.	3.95	0.964
[HA2] I am addicted to using same-day delivery apps.	3.34	1.261

The average mean score for all items relevant to habit was 3.84, suggesting that respondents generally agreed with the statements about habit. The highest level of agreement was with items HA4 ($\bar{x}$ = 4.03; s = 0.887) ("*Using same-day delivery apps has become second nature to me*") and HA1 ($\bar{x}$ = 4.02; s = 0.966) ("*The use of same-day delivery apps has become a habit of mine*"). From these results, it can be assumed that respondents agreed that purchasing through same-day delivery apps had become a habit, automated or second nature to them. Venkatesh et al. (2012: 161) state that habit influences consumers' behavioural intention to use a specific technology automatically, because of learning and previous experiences. The lowest level of agreement was with item HA2 ($\bar{x}$ = 3.34), which also showed the most variance from respondents (s = 1.261). The statement, "*I am addicted to using same-day delivery apps*", could have had a negative connotation for participants and they were perhaps reluctant to agree with a statement inferring an addiction; hence the high variability (s = 1.261). Respondents were therefore objective as to whether they were addicted to using same-day delivery apps.

6.3.1.7 Price value

The mean and standard deviation scores for the five scale items related to the price value construct are detailed in Table 6.10 and ranked according to the highest mean score. Scale items 5.8, 5.14, 5.25, 5.62 and 5.64 of the research instrument were used to measure the price value construct.

Table 6.10: Price value: Mean and standard deviation scores

Item	Item mean	Item std dev.
[PV1] The cost of using same-day delivery apps is reasonable.	4.18	0.846
[PV3] At the current price for using same-day delivery apps (such as Internet/data costs and smartphone maintenance), good value for money is provided.	4.09	0.865
[PV2] Same-day delivery apps offer good value for money.	4.06	0.888
[PV4] Using a same-day delivery app is worth the costs involved, such as the delivery and service fees.	4.04	0.869
[PV5] It is more expensive to purchase products through same-day delivery apps than physically going to the store.	3.20	1.242

Across all items, the average mean score was 3.91, which suggests that respondents generally agreed with the items relating to price value. The highest level of agreement was with item PV1 ($\bar{x}$ = 4.18; s = 0.846) ("*The cost of using same-day delivery apps is reasonable*") and item PV3 ($\bar{x}$ = 4.09; s = 0.865) (*"At the current price for using same-day delivery apps (such as Internet/data costs and smartphone maintenance), good value for money is provided"*). From the general agreement with the statements relevant to price value, it can be assumed that the majority of respondents agreed that the benefits of using same-day delivery apps were perceived to be greater than the monetary cost associated with using same-day delivery apps. This is in line with Gupta et al. (2018: 58), Tamilmani et al. (2018: 2) and Venkatesh et al. (2012: 161).

The lowest level of agreement was with item PV5 ($\bar{x}$ = 3.20) ("*It is more expensive to purchase products through same-day delivery apps than physically going to the store*"), which also carried the most variance (s = 1.242). The variance could be attributed to the fact that the cost of using same-day delivery apps cannot be compared to physically visiting a store, as different factors are at play. For instance, the use of same-day delivery apps involves data costs, service fees and delivery fees, whereas the costs associated with physically visiting a store include transportation and the consumer's time. The benefits received compared to the monetary cost involved could differ from one individual to the next as, for example, one person might be located closer to a store or have more flexible working hours than another person. Therefore, while one individual might consider the monetary loss to be trivial in their lifestyle and situation, another individual might consider it to be too high.

6.3.1.8 Lifestyle compatibility

The mean and standard deviation scores for the items related to the lifestyle compatibility construct are shown in Table 6.11. The responses were ranked according to the highest mean score.

Lifestyle compatibility was measured through the nine scale items 5.1, 5.11, 5.18, 5.33, 5.37, 5.40, 5.48, 5.53 and 5.61 in the research instrument.

Table 6.11: Lifestyle compatibility: Mean and standard deviation scores

Item	Item mean	Item std dev.
[LSC6] The use of same-day delivery apps is a necessity in today's world.	4.46	0.775
[LSC1] Using same-day delivery apps fits well into my lifestyle.	4.24	0.781
[LSC3] Same-day delivery apps are compatible with most aspects of my shopping activities.	4.24	0.740
[LSC5] I prefer using a same-day delivery app instead of physically going to a store.	4.23	0.875
[LSC2] Same-day delivery apps fit in well with how I like to do my shopping.	4.18	0.792
[LSC4] I regularly order products through same-day delivery apps.	4.08	0.889
[LSC8] Same-day delivery apps are an important source of information for me.	4.01	0.807
[LSC9] Life will be very boring without same-day delivery apps.	3.88	1.015
[LSC7] I cannot imagine my life without same-day delivery apps.	3.72	1.101

The average mean score for all items that relate to lifestyle compatibility was 4.12, indicating a general agreement with the statements about lifestyle compatibility. Although the results are quite evenly dispersed across the items, the slightly higher level of agreement was with item LSC6, with a mean score of 4.46 (s = 0.775) ("*The use of same-day delivery apps is a necessity in today's world*"). The higher agreement could be due to the worldwide COVID-19 pandemic which increased the demand for home deliveries and on-demand services, and owing to the civil unrest which occurred in South Africa at the time of data collection. On the other hand, the lowest level of agreement was with item LSC7 ($\bar{x}$ = 3.72; s = 1.101) ("*I cannot imagine my life without same-day delivery apps*") and item LSC9 ($\bar{x}$ = 3.88; s = 1.015) ("*Life will be very boring without same-day delivery apps*"). Items LSC7 and LSC9 also had the most variance (LSC7: s = 1.101; LSC9: s = 1.015). From the somewhat lower agreement with these two statements, it can be assumed that respondents were slightly more impartial as to whether they could live without same-day delivery apps, inferring that they were not dependent on same-day delivery apps. This finding is in line with the low agreement observed with HA2, discussed in section 6.3.1.6 above.

For the above discussion and results, it can be deduced that consumers typically agreed with the statements that same-day delivery apps were well suited to their lifestyle and daily routine, and largely fit in with the way in which they lived and conducted themselves socially. Respondents, however, were not dependent on same-day delivery apps. These results could be attributed to the COVID-19 pandemic and civil unrest situations consumers found themselves in during the time

the study was conducted and the increased need to maintain social distancing, avoid public and crowded places and refrain from entering areas with violent protest activities.

6.3.1.9 Perceived risk

The mean and standard deviation scores for each of the eight scale items relating to the perceived risk construct are presented in Table 6.12. The responses were ranked according to the highest mean score. Scale items 5.4, 5.15, 5.17, 5.28, 5.35, 5.51, 5.58 and 5.60 of the research instrument were used to measure the perceived risk construct.

Table 6.12: Perceived risk: Mean and standard deviation scores

Item	Item mean	Item std dev.
[PR3] I feel comfortable giving out payment information (such as credit card details) to transact on a same-day delivery app.	3.63	1.076
[PR6] There is a lot of uncertainty associated with purchasing products/services using same-day delivery apps.	3.27	1.186
[PR1] Providing personal information (such as my name, address and telephone number) on same-day delivery apps is risky.	3.17	1.184
[PR2] I am concerned that the information I submit on same-day delivery apps could be misused.	3.16	1.183
[PR7] The use of same-day delivery apps is riskier than other methods of purchasing products/services (such as personally visiting a store).	3.16	1.253
[PR8] I believe that the risk of purchasing products/services through same-day delivery apps is very high.	3.02	1.228
[PR5] Purchasing products/services through same-day delivery apps is risky.	2.95	1.207
[PR4] I feel apprehensive (anxious/nervous) about purchasing products/services through same-day delivery apps.	2.83	1.274

The average mean score across all items related to perceived risk was 3.15, indicating impartiality to the statements. The mean scores reported in Table 6.12, apart from PR3, illustrate that respondents were neutral towards the statements representing the perceived risk construct. The highest level of agreement, with a mean score of 3.63 (s = 1.076), was with item PR3 ("*I feel comfortable giving out payment information, such as credit card details, to transact on a same-day delivery app*"). The lowest level of agreement, with a mean score of 2.83 (s = 1.274), was with items PR4 ("*I feel apprehensive (anxious/nervous) about purchasing products/services through same-day delivery apps*") and PR5 ($\bar{x}$ = 2.95; s = 1.207) ("*Purchasing products/services through same-day delivery apps is risky*").

Illustrated by the fact that respondents reported neutrally towards the statements relating to perceived risk, it can be presumed that they felt exposed to risk when transacting on same-day

delivery apps. It is interesting to note that the highest level of agreement from participants was that they felt comfortable giving out payment information on same-day delivery apps, but still felt apprehensive in doing so. Respondents were somewhat unbiased towards the potential loss while shopping using mobile shopping apps compared to purchasing products or services offline. This could be due to the infancy of grocery-related same-day delivery apps in the South African market and consumers' ignorance of the potential risks involved in using same-day delivery apps. Belanche et al. (2020: 6) and Kaushik et al. (2020: 12) argue that users' concern for privacy and security on mobile shopping apps is a factor that can prevent the adoption of online or mobile shopping apps. Pauzi et al. (2017: 5) report that perceived risk refers to individuals' degree of doubt concerning the outcome of their decision in online purchasing. The high variability across all items could be attributed to respondents' uncertainty towards the use of same-day delivery apps and obliviousness of the risks involved in using these types of apps, perhaps due to their infancy in the South African market at the time of data collection, or due to the retailers already being well established in the South African market.

6.3.1.10 Perceived self-efficacy

Table 6.13 details the mean and standard deviation scores for each of the five scale items (items 5.10, 5.24, 5.30, 5.44 and 5.49) related to the perceived self-efficacy construct. The responses were ranked according to the highest mean score.

Table 6.13: Perceived self-efficacy: Mean and standard deviation scores

Item	Item mean	Item std dev.
[PSE1] I can use same-day delivery apps without the help of others.	4.53	0.714
[PSE3] I am confident that I can use same-day delivery apps successfully.	4.49	0.658
[PSE5] Overall, I am confident in using same-day delivery apps by myself.	4.48	0.644
[PSE2] I have enough knowledge and skills to use same-day delivery apps successfully.	4.45	0.681
[PSE4] I can use same-day delivery apps reasonably well on my own.	4.45	0.627

The average mean score for all items related to the perceived self-efficacy construct was 4.48, suggesting that respondents largely agreed with the statements about perceived self-efficacy and felt that they had the required knowledge, abilities and skills to use same-day delivery apps without the help of others. These results are in line with the literature stating that a higher level of perceived self-efficacy will lead to higher intentions to adopt and use technology (Moghavvemi et al., 2013: 247; Singh et al., 2018: 115).

Although the level of agreement was high with all scale items related to perceived self-efficacy, the highest level of agreement was with item PSE1 ($\bar{x}$ = 4.53; s = 0.714) ("*I can use same-day delivery apps without the help of others*"). This was closely followed by PSE3 ($\bar{x}$ = 4.49; s = 0.658) ("*I am confident that I can use same-day delivery apps successfully*") and PSE5 ($\bar{x}$ = 4.48; s = 0.644) ("*Overall, I am confident in using same-day delivery apps by myself*"). It is evident from the relatively high mean scores reported in Table 6.13 that many respondents felt confident in their own ability and self-confident to use same-day delivery apps successfully without the help of others. These results are also consistent with the results reported in Table 6.6 (FC1), signifying that respondents would rather become acquainted with the app on their own than obtain help from others. The results could be attributed to the sample already being competent in using smartphones, online shopping platforms and apps, and hence same-day delivery apps, as the majority of the sample was considered to be technologically adept.

6.3.1.11 Attitude towards use

Table 6.14 represents the mean and standard deviation of the six scale items used to measure attitude towards using a specific technology. The responses were ranked according to the highest mean score. The attitude towards use construct was measured by means of scale items 5.5, 5.27, 5.31, 5.39, 5.43 and 5.57 of the research instrument.

Table 6.14: Attitude towards use: Mean and standard deviation scores

Item	Item mean	Item std dev.
[ATT4] Overall, I am satisfied with same-day delivery apps.	4.40	0.722
[ATT2] I like using same-day delivery apps.	4.38	0.735
[ATT1] Using same-day delivery apps is a smart way to shop.	4.35	0.748
[ATT3] Using same-day delivery apps is a good idea.	4.34	0.669
[ATT6] I am in favour of purchasing products/services through same-day delivery apps.	4.25	0.730
[ATT5] In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services.	4.02	0.863

The average mean score across all items related to the attitude towards use construct was 4.29, which implies general agreement with this construct. The highest level of agreement, with a mean score of 4.40 (s = 0.722), was with item ATT4 ("*Overall, I am satisfied with same-day delivery apps*"), followed by item ATT2 with a mean score of 4.38 (s = 0.735) ("*I like using same-day delivery apps*"). The lowest agreement score ($\bar{x}$ = 4.02), which also had the most variance (s = 0.863), was with item ATT5 ("*In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services*"). From the generic agreement with all statements

related to this construct, it can be inferred that respondents had a favourable attitude towards the use of same-day delivery apps, as they generally enjoyed using same-day delivery apps and were satisfied with these types of apps. The literature suggests that a favourable attitude towards using technology will increase individuals' likelihood of adopting and using the specific technology (e.g. Al-Debei et al., 2013: 46; Heirman & Walrave, 2012: 614; Sanne & Wiese, 2018: 4).

Although a high mean score was recorded across all items related to attitude towards use, respondents were less in agreement as to whether same-day delivery apps were better to use than other methods of purchasing products and/or services (ATT5; $\bar{x}$ = 4.02). These results could be due to the emergent stage of many of the grocery-related same-day delivery apps in the South African market at the time of data collection, and respondents possibly still exploring these types of apps.

6.3.1.12 Behavioural intention

The mean and standard deviation of each of the six scale items used to measure the dependent variable – behavioural intention – are presented in Table 6.15. The responses were ranked according to the highest mean score. Question 6 of the research instrument measured the behavioural intention construct.

Table 6.15: Behavioural intention: Mean and standard deviation scores

Item	Item mean	Item std dev.
[BI1] I intend to continue using same-day delivery apps in the future.	4.43	0.705
[BI2] I plan to continue using same-day delivery apps frequently.	4.34	0.713
[BI5] I will recommend the use of same-day delivery apps to others.	4.33	0.706
[BI6] I intend to use same-day delivery apps more frequently going forward.	4.21	0.776
[BI3] I will always try to use same-day delivery apps in my daily life.	4.14	0.845
[BI4] I intend to continue using same-day delivery apps rather than using any alternative means.	3.99	0.903

Across all items, the average mean score was 4.24, which suggests that respondents generally agreed with the items about behavioural intention. Although the mean scores across all scale items measuring behavioural intention were relatively high, the highest level of agreement was with item BI1 ($\bar{x}$ = 4.43; *s* = 0.705) ("*I intend to continue using same-day delivery apps in the future*") and item BI2 ($\bar{x}$ = 4.34; *s* = 0.713) (*"I plan to continue using same-day delivery apps frequently"*), indicating the acceptance of same-day delivery apps and continual usage in the future. The lowest level of agreement, with a mean score of 3.99 (*s* = 0.903), was with item BI4 ("*I intend to continue using same-day delivery apps rather than using any alternative means*").

Many of the respondents agreed that they intended to use or continue using same-day delivery apps in the future, which is in line with the literature stating that an individual's intention to perform a specific behaviour is the best predictor of whether the individual will perform that behaviour (Ajzen, 1991 in Kendrick, 2011).

To summarise, many of the respondents who participated in the research study typically agreed with the statements presented in the research instrument relating to various factors potentially influencing consumers' behavioural intention to continue using same-day delivery apps. From the discussion above, it can be deduced that the individual scale items in the research instrument were meaningful to a sample of South Africa consumers as participants generally agreed with all the statements in the scale. Empirical research objective 2 was therefore achieved.

6.3.2 ASSUMPTIONS OF NORMALITY: SKEWNESS AND KURTOSIS

To further understand the nature of the distribution of data obtained, the shape of distribution (normality) was assessed by examining the skewness and kurtosis values of the 70 scale items related to the 11 independent variables (64 items) and dependent variable (6 items). Normality is required to ensure that multivariate statistical techniques, such as factor analysis, can be applied to the data. Normality of the dataset was expected given the large sample size (n = 485) which, according to Pallant (2016: 73), reduces the latent unfavourable effects of non-normality in data.

Skewness is a characteristic of a distribution that indicates the balance of the distribution of the data, by assessing its symmetry about the mean (Malhotra, 2019: 445). A lack of symmetry of the distribution about the arithmetic mean indicates that the distribution is skewed (Allen, 2018: 2). Positive skewness values suggest that scores are clustered to the left at the low values; while negative skewness values indicate a clustering of scores at the high end of a graph (Pallant, 2016: 73).

Kurtosis is a measure of the relative peakedness or flatness of the curve defined by the frequency distribution (Malhotra, 2019: 445). Positive kurtosis values indicate that the distribution is rather peaked (clustered in the centre), with long thin tails. Kurtosis values below 0 (≤ 0) indicate a relatively flat distribution (too many cases in the extremes) (Pallant, 2016: 73). The closer both the skewness and kurtosis values are to 0, the more normal the data distribution (Van Niekerk, 2020: 251). Barry et al. (2011: 103) state that data are normally distributed if the skewness and kurtosis lie in the range of -2 and +2.

Table 6.16 summarises the skewness and kurtosis for each of the 70 scale items in the research instrument.

Table 6.16: Skewness and kurtosis

Scale item	Skewness	Kurtosis
[PE1] Using same-day delivery apps frees up time, allowing me to do something else, and therefore increases my productivity.	-1.403	2.847
[PE2] Using same-day delivery apps help me accomplish my shopping goals faster.	-1.301	2.315
[PE3] Using same-day delivery apps allow me to achieve things that are important to me while I wait for products to be delivered.	-1.179	1.805
[PE4] Same-day delivery apps are beneficial to me.	-0.744	0.959
[PE5] I find same-day delivery apps useful in my daily life.	-0.840	0.826
[PE6] I can save time when I use same-day delivery apps to purchase products.	-0.987	1.573
[EE1] Learning how to use same-day delivery apps is easy for me.	-1.458	3.541
[EE2] It is easy for me to become skilful in using same-day delivery apps.	-0.581	-0.053
[EE3] I find same-day delivery apps easy to use.	-1.153	2.326
[EE4] The way I interact with same-day delivery apps is clear and understandable.	-1.262	2.980
[EE5] Same-day delivery apps require minimal effort from me.	-1.337	2.494
[FC1] I can get help from others when I have difficulties using same-day delivery apps.	-0.965	1.066
[FC2] Same-day delivery apps are compatible with other technologies I use.	-0.921	1.481
[FC3] I have the knowledge necessary to use same-day delivery apps.	-0.940	1.091
[FC4] I have the resources necessary to use same-day delivery apps.	-1.474	3.138
[FC5] I feel comfortable using same-day delivery apps.	-0.645	-0.020
[SI1] People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps.	-0.791	0.316
[SI.2] People whose opinions I value use same-day delivery apps.	-0.665	0.192
[SI3] People who influence my behaviour think that I should use same-day delivery apps.	-0.534	-0.304
[SI4] Friends' suggestions and recommendations affect my decision to use same-day delivery apps.	-0.472	-0.653
[SI5] Family members influence my decision to use same-day delivery apps.	-0.373	-0.700
[SI6] Mass media (such as TV, radio, magazines and social media) influence my decision to use same-day delivery apps.	-0.711	-0.083
[HM1] Using same-day delivery apps is fun.	-0.645	0.190
[HM2] Using same-day delivery apps is enjoyable.	-1.037	1.866
[HM3] Using same-day delivery apps is very entertaining.	-0.581	0.004
[HM4] Using same-day delivery apps is interesting.	-0.980	1.754
[HM5] I experience pleasure when using same-day delivery apps.	-0.799	0.809
[HA1] The use of same-day delivery apps has become a habit of mine.	-0.930	0.404
[HA2] I am addicted to using same-day delivery apps.	-0.268	-1.003
[HA3] I must use same-day delivery apps.	-0.766	0.114
[HA4] Using same-day delivery apps has become second nature to me.	-0.846	0.575
[PV1] The cost of using same-day delivery apps is reasonable.	-1.157	1.687
[PV2] Same-day delivery apps offer good value for money.	-0.910	0.699

Scale item	Skewness	Kurtosis
[PV3] At the current price for using same-day delivery apps (such as Internet/data costs and smartphone maintenance), good value for money is provided.	-1.013	1.203
[PV4] Using a same-day delivery app is worth the costs involved, such as the delivery and service fees.	-0.973	1.012
[PV5] It is more expensive to purchase products through same-day delivery apps than physically going to the store	-0.146	-1.000
[LSC1] Using same-day delivery apps fits well into my lifestyle.	-1.030	1.115
[LSC2] Same-day delivery apps fit in well with how I like to do my shopping.	-1.108	1.997
[LSC3] Same-day delivery apps are compatible with most aspects of my shopping activities.	-0.821	0.702
[LSC4] I regularly order products through same-day delivery apps.	-1.083	1.275
[LSC5] I prefer using a same-day delivery app instead of physically going to a store.	-1.270	1.850
[LSC6] The use of same-day delivery apps is a necessity in today's world.	-1.706	3.590
[LSC7] I cannot imagine my life without same-day delivery apps.	-0.687	-0.248
[LSC8] Same-day delivery apps are an important source of information for me.	-0.564	0.048
[LSC9] Life will be very boring without same-day delivery apps.	-0.798	0.335
[PR1] Providing personal information (such as my name, address and telephone number) on same-day delivery apps is risky.	-0.132	-0.915
[PR2] I am concerned that the information I submit on same-day delivery apps could be misused.	-0.149	-0.864
[PR3] I feel comfortable giving out payment information (such as credit card details) to transact on a same-day delivery app.	-0.627	-0.183
[PR4] I feel apprehensive (anxious/nervous) about purchasing products/services through same-day delivery apps.	0.213	-1.035
[PR5] Purchasing products/services through same-day delivery apps is risky.	0.031	-0.907
[PR6] There is a lot of uncertainty associated with purchasing products/ services using same-day delivery apps.	-0.203	-0.895
[PR7] The use of same-day delivery apps is riskier than other methods of purchasing products/services (such as personally visiting a store).	-0.128	-1.061
[PR8] I believe that the risk of purchasing products/services through same-day delivery apps is very high.	0.020	-1.026
[PSE1] I can use same-day delivery apps without the help of others.	-1.942	5.121
[PSE2] I have enough knowledge and skills to use same-day delivery apps successfully.	-1.371	2.916
[PSE3] I am confident that I can use same-day delivery apps successfully.	-1.470	3.497
[PSE4] I can use same-day delivery apps reasonably well on my own.	-0.860	0.448
[PSE5] Overall, I am confident in using same-day delivery apps by myself.	-1.167	1.923
[ATT1] Using same-day delivery apps is a smart way to shop.	-1.248	2.167
[ATT2] I like using same-day delivery apps.	-1.254	2.247
[ATT3] Using same-day delivery apps is a good idea.	-0.978	2.070
[ATT4] Overall, I am satisfied with same-day delivery apps.	-1.470	3.518
[ATT5] In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services.	-0.682	0.171
[ATT6] I am in favour of purchasing products/services through same-day delivery apps.	-0.768	0.413
[BI1] I intend to continue using same-day delivery apps in the future.	-1.283	2.262
[BI2] I plan to continue using same-day delivery apps frequently.	-0.936	0.764
[BI3] I will always try to use same-day delivery apps in my daily life.	-0.936	0.878
[BI4] I intend to continue using same-day delivery apps rather than using any alternative means.	-0.597	-0.271

Scale item	Skewness	Kurtosis
[BI5] I will recommend the use of same-day delivery apps to others.	-1.098	2.273
[BI6] I intend to use same-day delivery apps more frequently going forward.	-0.748	0.258

Table 6.16 lists the skewness and kurtosis values of the 70 scale items used in the measuring instrument. While non-normality in item distributions was observed, analysing skewness and kurtosis alongside established statistical tests offered valuable insights into consumer intentions. In general, negative skewness emerged across many items, suggesting a tendency towards positive intentions. Consumers perceive same-day delivery apps as beneficial, time-saving, and easy to use, integrating well into their lifestyles. Items relating to skill confidence and perceived value supported this favourable perception, with the majority believing they could use these apps effectively and that they were worth the cost.

Kurtosis values revealed that several items had peaked distributions, indicating great agreement on key variables such as learnability and compatibility with existing shopping patterns. In contrast, categories such as social impact and risk perception showed greater variability, indicating that individual experiences and attitudes about peer pressure and security concerns differ greatly. Furthermore, items pertaining to habit formation and necessity did not exhibit significant skewness, implying that while many appreciate the convenience of same-day delivery, it has not yet become an essential habit for most consumers. While risk perception regarding privacy and security was not a major theme, the absence of significant skewness and negative kurtosis in these areas suggests room for improvement. Addressing these concerns may strengthen customer trust and encourage even higher adoption rates.

While a negative skewness (clustering at the end side of the scale) was detected for numerous items, as highlighted in Table 6.16, it has been shown that with reasonably large samples (≥ 100), skewness will not make a substantive difference in the analysis (Tabachnick & Fidell, 2019: 80). Evidence of both positive and negative kurtosis was also found. While kurtosis may result in an underestimate of the variance, the risk associated with high levels of kurtosis is reduced in samples exceeding 200 (Tabachnick & Fidell, 2019: 80). The large sample size (n = 485) thus reduced the potentially detrimental effects of non-normality in the data (Pallant, 2016: 73). The assumption of normality was, however, met and it was considered appropriate to proceed with factor analysis.

6.4 FACTOR ANALYSIS

Factor analysis, according to Frankfort-Nachmias et al. (2015: 396), is a statistical technique for classifying a large number of interrelated variables into a limited number of dimensions or factors. Generally, factor analysis serves several related functions, namely to identify underlying dimensions or factors that explain the correlation among a set of variables, to condense information by providing a means of explaining variation among variables using newly created variables or factors, to define the substantive content or meaning of the factor that accounts for variation among a larger set of items and to aid in identifying items that do not fit into any of the factorially derived categories of items, or that fit into more than one of these categories (DeVellis, 2017: 155; Malhotra, 2019: 582).

Factor analysis can be explored using exploratory factor analysis (EFA) and/or confirmatory factor analysis (CFA). EFA is used to identify underlying dimensions or factors that explain the correlations among a set of variables (Malhotra, 2019: 681), and CFA seeks to confirm if the number of factors and the loadings of observed variables conform to what is expected based on theory (Malhotra, 2019: 667). Therefore, while EFA is a theory-generating procedure, CFA is a theory-testing procedure (Reinecke & Pöge, 2020: 3).

For the purpose of the research study, EFA was not conducted because preconceived ideas regarding the underlying dimensions were readily available and linked to theoretical assumptions and reasoning. These preconceived ideas were illustrated in the conceptually derived model (refer to Chapter 4, Figure 4.1) and underlying theory discussed in Chapters 3 and 4. The results of the CFA are discussed in the next section.

6.4.1 CONFIRMATORY FACTOR ANALYSIS – DEVELOPING AN EMPIRICAL MODEL FOR CONSUMERS' BEHAVIOURAL INTENTION

CFA was conducted to test the extent to which *a priori* theoretical patterns of factor loadings on prespecified constructs represent the actual data (Hair et al., 2014a: 603). CFA was used to assess and confirm if the collected data fit the specified conceptual model as developed from a theoretical base (Venter & Van Zyl, 2017: 176). CFA was therefore used to achieve empirical research objective 3: to assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention. The CFA process that was followed to assess

the proposed measurement model is shown in Figure 6.2 and discussed in the remainder of this section.

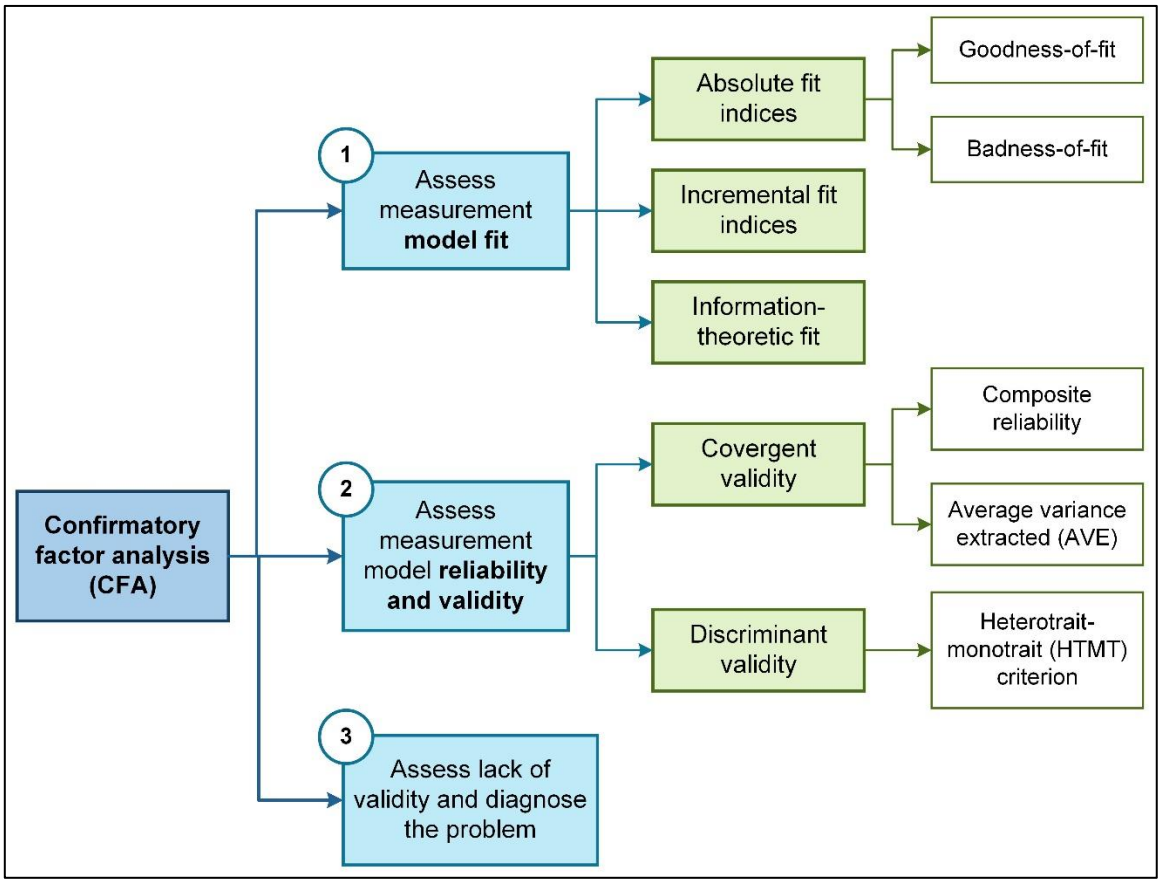

Figure 6.2: CFA process of assessing the measurement model

Source: Author's own compilation

The validity of the measurement model depends firstly on the goodness-of-fit results and, secondly, on the reliability and evidence of construct validity, especially convergent and discriminant validity, as shown in Figure 6.2. The first step of CFA was therefore to explore how well the sample data fit the observed constructs in the theorised conceptual model. The model fit indices and the results are reported in the following section.

6.4.1.1 Assess the measurement model's fit

Many measures of overall model fit have been developed, each one indicating whether the modelled relationships between the latent and observed constructs replicate the relationships between the observed variables in the data. Goodness-of-fit measures describe how well the observed data represents the latent constructs of interest (Wesolowski, 2018: 2), and badness-of-fit indices measure errors or deviations (Malhotra, 2019: 673). Good-fitting models, according to

Tabachnick and Fidell (2013: 725), produce consistent results on many different indices. If the results of the fit indices are inconsistent, the model should be re-examined. The model fit indices applied in the research study were explained in Chapter 5, section 5.2.7.2.1 and Table 5.13.

The various goodness-of-fit indices used to assess the conceptual model for the 11 independent constructs underlying behavioural intention (dependent construct) are shown in Table 6.17.

Table 6.17: Model fit for the original model (12 constructs; 70 scale items)

Goodness-of-fit indices	Original model	Prescribed threshold
Absolute fit indices		
Chi square (CMIN)	**6383.40**	*p* ≥ 0.05 (Kirsten, 2019: 569)
Degrees of freedom (*df*)	**2279**	
p-value	≤ 0.001	≥ 0.05 (Awang, 2012: 56; Hu & Bentler, 1999: 27)
Chi square/df (CMIN/df)	**2.801**	≤ 3 (Awang, 2012: 56; Hu & Bentler, 1999: 27)
Goodness-of-fit index (GFI)	0.68	> 0.90 (Awang, 2012: 56; Gupta & Singh, 2015: 10; Schumacker & Lomax, 2010: 76)
Root mean square error of approximation (RMSEA)	**0.061**	< 0.05 - 0.08 (Gupta & Singh, 2015: 11; Schumacker & Lomax, 2010: 76)
Standardised root mean square residual (SRMR)	0.081	≤ 0.08 - 0.10 (Hair et al., 2014a: 579)
Adjusted goodness-of-fit index (AGFI)	0.65	> 0.80 (Gupta & Singh, 2015: 10; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012)
Incremental/relative fit indices		
Normed fit index (NFI)	0.73	≥ 0.90 (Awang, 2012: 56; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012; Newsom, 2018: 2; Schumacker & Lomax, 2010: 76)
Tucker Lewis index (TLI)	0.80	
Comparative fit index (CFI)	0.81	
Information-theoretic fit indices		
Akaike's information criterion (AIC)	6 795.4	Min./small (Schumacker & Lomax, 2010: 76; Wu et al., 2019: 8)
Bayesian information criterion (BIC)	7 657.3	

The results in Table 6.17 provide an overview of the overall model fit. Primarily, the absolute fit and incremental fit indices were explored to assess the overall model fit. Three absolute fit indices (CMIN/*df*, RMSEA and SRMR) revealed an acceptable model fit. The CMIN/*df* value, which is used to reduce the dependency on sample sizes, revealed a good model fit with an acceptable value of 2.801 (CMIN/*df* ≤ 3). The RMSEA highlights "… the difference between the observed covariance matrix per degree of freedom and the hypothesised covariance matrix which demotes

the model" (Van Niekerk, 2020: 257). An RMSEA value of between 0.05 and 0.08 is regarded as an acceptable fit (Schumacker & Lomax, 2010: 76). As is evident from the results, the RMSEA test achieved a fit index of 0.061, indicating an acceptable fit (Newsom, 2018: 3). Furthermore, SRMR was assessed to compare fit across models (Hair et al., 2014a: 579). SRMR is considered acceptable if the value is ≤ 0.08, but not more than 0.10 (Hair et al., 2014a: 579). SRMR achieved a fit index of 0.081, indicating an adequate model fit. Hair et al. (2014a: 584), however, advise that for a sample size of more than 250 and more than 30 observed variables, an SRMR value of 0.08 or less is only acceptable if the CFI is above 0.92, which was not achieved in this assessment (CFI = 0.68). As a result, the SRMR indicated a misfit.

The GFI obtained was 0.68 as against the recommended value of above 0.90 (Awang, 2012: 56), and the AGFI was 0.65 as against the recommended value of above 0.80 (Gupta & Singh, 2015: 10). The NFI, TLI and CFI were 0.73, 0.80 and 0.81, respectively, compared to the recommended level of above 0.90 (Awang, 2012: 56; Newsom, 2018: 2; Schumacker & Lomax, 2010: 76). AIC and BIC indices appear to be high, but were re-assessed against the adjusted model discussed in section 6.4.2 below.

The measurement model indicated a mediocre to poor fit. There was thus a significant discrepancy between the conceptual model proposed in Chapter 4 (Figure 4.1) and the correlations observed in the measurement model. Consequently, the theorised model did not fit well with the observed data.

The standardised regression weights as well as the correlation estimates of the original model can be found in Annexure H.

The second step in the CFA process, as shown in Figure 6.2, is to assess the reliability and validity of the measurement model to explore the reliability and validity that are unique to SEM. The results are discussed in the next section.

6.4.1.2 Assess the reliability and validity of the measurement model

To assess the validity unique to SEM, construct validity is explored. Construct validity represents the degree to which inferences can justifiably be made to the theoretical constructs on which the operationalisations in the study were based (Venter & Van Zyl, 2017: 150). Construct validity is therefore established by relating the research instrument to the general theoretical framework within which the researcher conducts their study, to determine whether the instrument is logically and empirically tied to the concepts and theoretical assumptions employed (Frankfort-Nachmias

et al., 2015: 133). Construct validity generally has two sub-levels, namely convergent validity and discriminant validity (Dilbeck, 2018: 3), which are addressed below.

6.4.1.2.1 Convergent validity

Convergent validity, according to Malhotra (2019: 279), is the degree to which the scale positively correlates with other measures of the same construct. It therefore reflects the extent to which an item shows a positive association with other items of the same construct (Vellnagel, 2019: 83). The similarity of items in a measurement scale is thus revealed, demonstrating an adequately strong relationship between these items in the construct (Vellnagel, 2019: 83).

Convergent validity is commonly measured by exploring the composite reliability and AVE of each of the observed variables in the theorised model. Composite reliability is a measure of internal consistency in scale items, much like Cronbach's alpha coefficient (Netemeyer, Bearden & Sharma, 2003: 11). Malhotra (2019: 667) describes composite reliability as being equal to the total amount of true score variance relative to the total score variance. It is therefore an indicator of the shared variance among the observed variables used as an indicator of a latent construct (Fornell & Larcker, 1981: 46). Hair, Sarstedt, Hopkins and Kuppelwieser (2014b: 111) argue that composite reliability provides more appropriate measures of internal consistency reliability because it does not assume that all item loadings are equal in the population like the Cronbach alpha coefficient, and Cronbach's alpha is sensitive to the number of items in the scale and generally tends to underestimate internal consistency reliability. Ideally, composite reliability values should exceed 0.70, but values between 0.60 and 0.70 are considered acceptable in exploratory research (Hair et al., 2011: 140; Hamid et al., 2017: 2; Lin et al., 2020: 3).

An alternative method that is used to assess convergent validity is to explore the average variance extracted (AVE), which, according to Malhotra (2019: 676), is the amount of variance in the observed variables that are explained by the latent construct. AVE is a measure to determine the amount of variance captured by a construct in relation to the variance due to measurement error. The AVE value should exceed 0.50 so that it is considered adequate for convergent validity (Hamid et al., 2017: 2). An AVE of 0.50 or more indicates satisfactory convergent validity, meaning that the latent construct accounts for 50% or more of the variance in the observed variables, on average (Malhotra, 2019: 676).

Table 6.18 reports the results of the construct validity assessment, by summarising the composite reliability and AVE values of each of the observed constructs in the hypothesised model.

Table 6.18: Construct validity assessment of the hypothesised model – Composite reliability and AVE

Construct	Composite reliability	Average variance extracted (AVE)
Performance expectancy	0.858	**0.502**
Effort expectancy	0.805	0.456
Facilitating conditions	0.751	0.394
Social influence	0.836	0.464
Hedonic motivation	0.853	**0.538**
Habit	0.799	0.499
Price value	0.706	0.420
Lifestyle compatibility	0.881	0.455
Perceived risk	0.843	0.449
Perceived self-efficacy	0.858	**0.548**
Attitude towards use	0.840	0.467
Behavioural intention	0.893	**0.582**

Note: Composite reliability (≥ 0.70)
AVE (≥ 0.50)

Table 6.18 reveals acceptable composite reliability values for all observed variables as the composite reliability exceeds the recommended threshold of ≥ 0.70 (Hair et al., 2011: 140; Hamid et al., 2017: 2; Lin et al., 2020: 3). A high alpha value over several observed variables could, however, indicate that the items representing each observed construct are interchangeable and can be argued to correlate with each other. High composite reliability scores across all observed variables can therefore be an indication of a lack of discriminant validity, which will be explored in the next section.

The AVE value of performance expectancy (AVE: 0.502), hedonic motivation (AVE: 0.538), perceived self-efficacy (AVE: 0.548) and behavioural intention (AVE: 0.582) is satisfactory with values over the prescribed threshold of ≥ 0.50 (Malhotra, 2019: 676). However, effort expectancy, facilitating conditions, social influence, habit, price value, lifestyle compatibility, perceived risk and attitude towards use revealed unacceptable AVE scores with values less than the prescribed threshold of ≥ 0.50.

Fornell and Larcker (1981: 46) argue that AVE is a more conservative measure than composite reliability, as based on the composite reliability assessment alone, the researcher may conclude that the convergent validity of the construct is adequate, even though more than 50% of the variance is due to error. Based on Fornell and Larcker's premise, the validity of the individual observed variables as well as the construct of the measurement model is questionable, and a lack of discriminant validity is possible.

6.4.1.2.2 Discriminant validity

Contrary to convergent validity, discriminant validity refers to the extent to which a measure does not correlate with other constructs from which it is supposed to differ (Malhotra, 2019: 279). Discriminant validity explores whether measures that are intended to be different are in fact different and do not relate to one another (Saunders et al., 2016: 451; Van Niekerk, 2020: 264). For discriminant validity to be met, Henseler et al. (2015: 121) recommend a more stringent assessment of the observed variables using the Heterotrait-monotrait (HTMT) criterion assessment. Henseler et al. (2015: 121) state that the HTMT criterion assesses the average of the correlations of indicators across constructs measuring different phenomena, relative to the average of the correlations of indicators within the same construct. Their HTMT criterion suggests that all variables are distinctively different at a threshold of below 0.85 (≤ 0.85) for strict and below 0.90 (≤ 0.90) for liberal discriminant validity. For the purpose of this assessment, a strict discriminant validity threshold was desired (≤ 0.85).

Table 6.19 displays the results of the model's discriminant validity through the HTMT criterion assessment.

Table 6.19: Discriminant validity assessment of the hypothesised model: Heterotrait-monotrait (HTMT) criterion

Construct	Performance expectancy	Effort expectancy	Facilitating conditions	Social influence	Hedonic motivation	Habit	Price value	Lifestyle compatibility	Perceived risk	Perceived self-efficacy	Attitude towards use	Behavioural intention
PE												
EE	0.896**											
FC	0.988	1.041										
SI	**0.546***	**0.439***	**0.558***									
HM	**0.838***	**0.806***	0.862**	**0.653***								
HA	**0.835***	**0.673***	**0.760***	**0.753***	0.869**							
PV	0.892**	0.852**	0.962	**0.723***	0.912	0.894**						
LSC	0.935	**0.818***	0.914	**0.693***	0.928	0.990	0.946					
PR	**0.132***	**0.111***	**0.043***	**0.373***	**0.019***	**0.144***	**0.249***	**0.031***				
PSE	0.861**	0.990	0.980	**0.303***	**0.684***	**0.563***	**0.693***	**0.735***	**0.244***			
ATT	0.984	0.907	0.989	**0.602***	0.889**	**0.848***	0.914	0.976	**0.097***	0.880**		
BI	0.854**	**0.745***	**0.809***	**0.565***	**0.780***	**0.792***	**0.780***	**0.859****	**0.051***	**0.641***	**0.844***	

Key: Performance expectancy (PE); Effort expectancy (EE); Facilitating conditions (FC); Social influence (SI); Hedonic motivation (HM); Habit (HA); Price value (PV); Lifestyle compatibility (LSC); Perceived risk (PR); Perceived self-efficacy (PSE); Attitude towards use (ATT); Behavioural intention (BI)

Note: *Strict discriminant validity threshold (≤ 0.85);

**Liberal discriminant validity threshold (≤ 0.90)

A lack of discriminant validity is evident from the results reported in Table 6.19. It is apparent that measures are not significantly different from one another and, as a result, are highly correlated with one another. Lack of discriminant validity is detected with all observed constructs except for social influence, perceived risk and behavioural intention, with HTMT values below the stringent acceptable threshold of ≤ 0.85 (Henseler et al., 2015: 121). The results further indicate that performance expectancy, effort expectancy, facilitating conditions, hedonic motivation, habit, price value, lifestyle compatibility, perceived self-efficacy and attitude towards use are not distinctly different, with values above the stringent acceptable threshold of 0.85 (Henseler et al., 2015: 121). The probable explanation for the lack of discriminant validity likely stems from the challenges in achieving conceptual clarity and distinctiveness between the measures of these constructs. The results of the HTMT analysis imply that the observed constructs are not distinctly different from one another, which refutes the discriminant validity of the measurement model.

A lack of discriminant validity among these observed constructs, in the context of the research study and among the sampled population, could be attributed to the widespread proliferation of the Internet and mobile technologies, which implies that respondents were more familiar with different mobile technologies, they had mastered the basic skills of using mobile devices and shopping apps, they had the required resources and infrastructure (such as a working Internet connection and mobile data) to use same-day delivery apps and they generally inferred certain beneficial qualities with purchasing via mobile shopping apps. Individuals are more connected, adaptable to change and open to new technology, and therefore new apps are learnt quickly and related problems can be resolved independently by the user due to their technological expertise (Van Niekerk, 2020: 272). In the research study, all respondents were required to own a smartphone and use same-day delivery apps. Escobar-Rodriquez and Carvajal-Trujilo (2013: 63) further argue that individuals become accustomed to using mobile apps to the point where the apps are fully integrated into their daily lives and they become habituated to using mobile apps. It is apparent that the same can be inferred in this South African research study and among the sampled population. Respondents were acquainted with various technologies and consequently more capable of learning how same-day delivery apps work, and comfortable with using same-day delivery apps as they had the confidence, skills, knowledge and resources to do so.

Furthermore, a lack of discriminant validity between the observed constructs could be attributed to the COVID-19 pandemic and lockdown restrictions respondents found themselves in at the time the study was conducted, as well as the civil unrest which took place because of the imprisonment of former President Jacob Zuma for contempt of court. Respondents might have viewed the sacrifices of using same-day delivery apps as trivial against the need for social distancing, avoiding crowded spaces and avoiding violent riot areas, such as retail stores.

Due to the mediocre model fit indices, unsatisfactory convergent validity results and lack of discriminant validity observed in the theorised conceptual model presented in Chapter 4 (Figure 4.1), modifications had to be made to the measurement model. Remedial action taken to diagnose the problems observed above are addressed next.

6.4.1.3 Lack of validity – diagnosing the problem

In an attempt to remedy the lack of validity of the measurement model, diagnostic information provided by the CFA was analysed to make appropriate modifications to the model. The diagnostic cues that were used included exploring or assessing the path estimates or loadings, the standardised residual covariances, the modification indices and the specification search (Malhotra, 2019: 677). Consequently, 38 Likert scale items were removed from the original measurement model to improve the model fit. The scale items that were removed from the measurement model are listed in Table 6.20.

Table 6.20: Likert scale items removed from the measurement model to improve model fit

Construct	Likert scale items removed[#]
Performance expectancy	PE2; PE4; PE5; PE6
Effort expectancy	EE1; EE4; EE5
Facilitating conditions	FC1; FC3; FC4; FC5
Social influence	SI4; SI5; SI6
Hedonic motivation	HM2; HM3; HM4; HM5
Habit	HA2; HA4
Price value	PV3; PV5
Lifestyle compatibility	LSC1; LSC2; LSC3; LSC5; LSC6; LSC7; LSC9
Perceived risk	PR2; PR3; PR4
Perceived self-efficacy	PSE1; PSE2; PSE3; PSE4; PSE5
Attitude towards use	ATT4

Notes: [#]Refer to Annexure C for a complete list of statements used in the research instrument.

Source: Author's own compilation

Of the 11 independent variables that were proposed to significantly influence consumers' behavioural intention to continue using same-day delivery apps (see Chapter 1, Figure 1.3 and Chapter 4, Figure 4.1), only two constructs appeared to be noteworthy in the context of the research study – social influence (hypothesis 4) and perceived risk (hypothesis 9). Consequently, the foundational framework applied in the research study (the UTAUT2 Model), apart from social influence, is irrelevant in the context of the research study. By implication, the following hypotheses, as theorised in the development of the conceptual model (see Chapter 4), could not be verified empirically:

Hypothesis 1: There is a significant relationship between performance expectancy and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 2: There is a significant relationship between effort expectancy and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 3: There is a significant relationship between facilitating conditions and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 5: There is a significant relationship between hedonic motivations and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 6: There is a significant relationship between habit and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 7: There is a significant relationship between price value and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 8: There is a significant relationship between lifestyle compatibility and consumers' behavioural intention to continue using same-day delivery apps.

Hypothesis 10: There is a significant relationship between perceived self-efficacy and consumers' behavioural intention to continue using same-day delivery apps

Hypothesis 11: There is a significant relationship between a positive attitude towards same-day delivery apps and consumers' behavioural intention to continue using same-day delivery apps.

The revised measurement model will be presented and assessed in the next section.

6.4.2 REVISED MEASUREMENT MODEL FOR EXPLORING CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

Upon review of the initial measurement model, as discussed in the previous section (section 6.4.1), it is apparent that measures from the original conceptual model were not significantly different from one another and, as a result, were highly correlated with one another. A lack of discriminant validity was evident between all observed variables except for social influence, perceived risk and the dependent variable (behavioural intention). After assessing the diagnostic information provided by the CFA, modifications were made to the measurement model to generate a revised model that more adequately fits the data.

Three of the originally observed constructs prevailed, namely social influence, perceived risk and behavioural intention, although some scale items were removed to improve the validity of the

model (refer to Table 6.20 above). Additionally, 17 remaining scale items' path estimates or factor loadings clustered under a new latent variable that was labelled, based on theoretical justification, 'perceived customer value'. Perceived customer value is contextualised as the consumers' overall assessment of product or service utility based on varied benefits and sacrifices (Zeithaml, 1988 in Chahal & Kumari, 2012: 168). More specifically, perceived customer value can be regarded as a trade-off between perceived benefits and perceived losses (Hsu & Lin, 2015: 48).

Chang and Dibb (2012: 256) state that perceived customer value is strongly correlated with price, quality, sacrifice and satisfaction. Jansri (2018: 1) concurs, maintaining that values are useful predictors of behaviour because consumers decide to purchase a product after considering multiple consumption values, such as enjoyment, quality, cost-effectiveness and their trade-offs. The remaining 17 scale items that clustered under the new construct resembled the notions that same-day delivery apps increase an individual's productivity by allowing them to do things that are important, and they are easy to use, a good idea and cost-effective. It can be inferred that the trade-off between the sacrifices made by using same-day delivery apps outweighs the benefits and satisfaction received from using these particular apps. Therefore, it was deemed suitable to label the new construct as perceived customer value to describe the new cluster of scale items.

Chahal and Kumari (2012: 168) claim that perceived value significantly influences behavioural intention, and therefore exploring its dimensions can provide insight to providers in understanding consumers and maintaining sustainable relationships. Hsiao, Chang and Tang (2016: 345) concur, stating that perceived customer value should be investigated as a multidimensional approach to sufficiently capture the presence of both cognitive (functional and economic) and affective (emotional, social and epistemic) factors. The effect of multiple value dimensions should be taken into consideration concurrently as predictors of behaviour. It is anticipated and proposed that the perceived benefits derived from using same-day delivery apps can be viewed in terms of functional value (performance, ease of use and specific outcomes), economic value (monetary and value for money), emotional value (affective, enjoyment, pleasure and passion) and epistemic value (novelty, open-mindedness and curiosity).

The revised measurement model for the remaining constructs and items underlying behavioural intention is depicted in Figure 6.3 below. The magnitude of the standardised path coefficient estimates between the independent and dependent variables was also considered. All standardised path coefficients reflect the amount of change in the dependent variable that may be attributed to a change equal to a single standard deviation in the predictor variable (Kirsten, 2019: 818). The standardised estimates were used to evaluate the relative contribution of each predictor variable to each outcome variable in the model. The path diagram with parameter estimates,

presented in Figure 6.3, was produced based on the results of the CFA. All standardised path coefficients were significant at the 5% level of significance ($p \leq 0.05$).

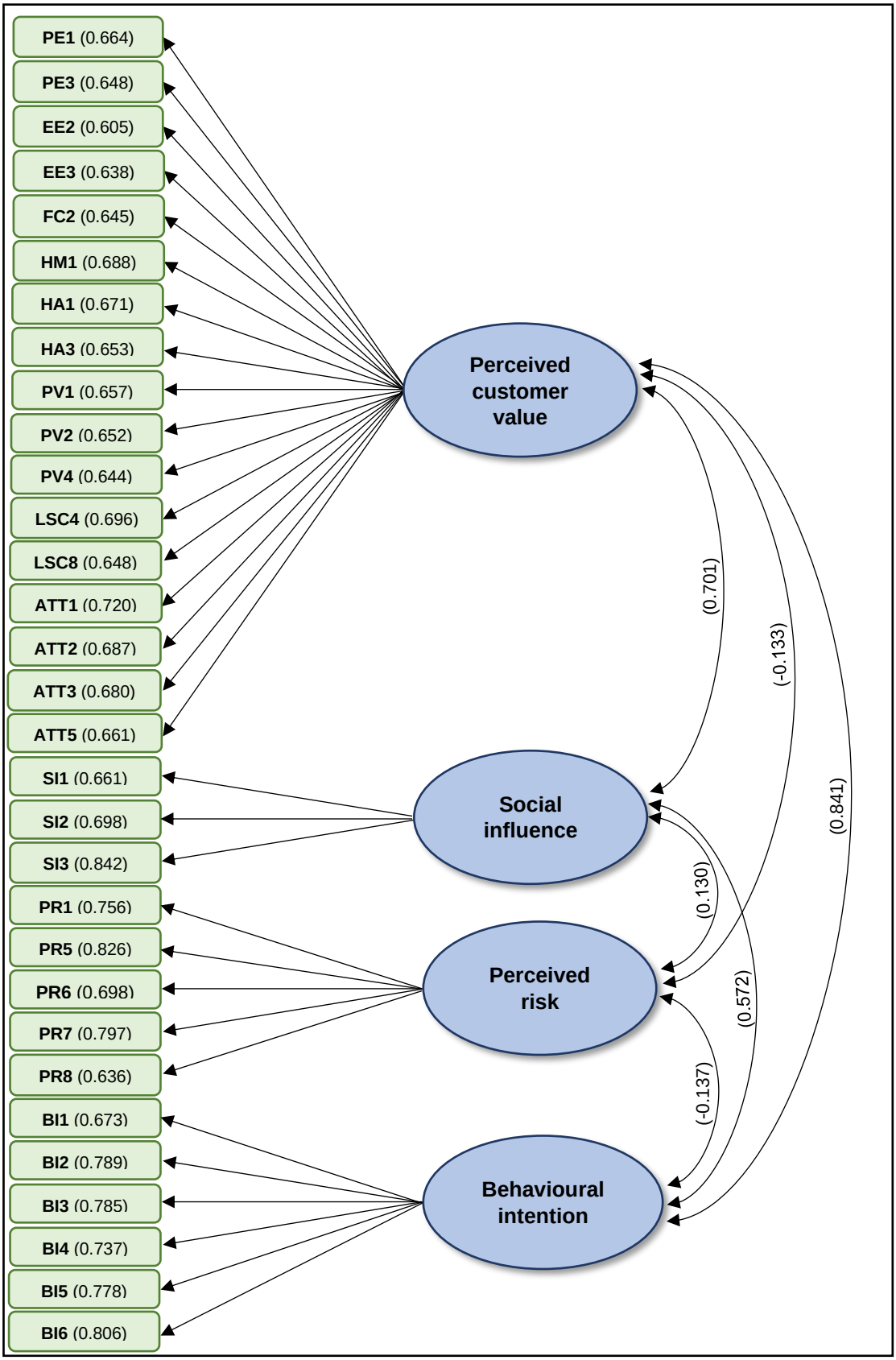

Figure 6.3: Revised measurement model

The revised measurement model was subjected to an assessment of the goodness-of-fit indices, and reliability and validity assessment, to establish whether the revised measurement model more adequately fit the data. The results of the assessment are discussed in the next section.

6.4.2.1 Model fit assessment of revised measurement model

The revised measurement model was subjected to further CFA to assess the model fit, reliability and validity.

The various goodness-of-fit indices used to assess the revised model for the three remaining constructs underlying behavioural intention – namely social influence, perceived risk and perceived customer value – compared to the original conceptual model are listed in Table 6.21. On adjusting the model and removing several Likert scale items, the model fit improved significantly, indicating that the revised measurement model fit the data well.

Table 6.21: Comparison of model fit for the original and revised models (4 constructs; 31 scale items)

Goodness-of-fit measures	Original model fit outcomes	Revised model fit outcomes	Acceptable fit threshold
Absolute fit indices			
Chi square (CMIN)	6383.40	**1080.78**	p ≥ 0.05 (Kirsten, 2019: 569)
Degrees of freedom (*df*)	2279	**428**	
p-value	< 0.001	< 0.001	≥ 0.05 (Awang, 2012: 56; Hu & Bentler, 1999: 27)
Chi square/df (CMIN/*df*)	2.801	**2.525**	≤ 3 (Awang, 2012: 56; Hu & Bentler, 1999: 27)
Goodness-of-fit index (GFI)	0.68	0.86	> 0.90 (Awang, 2012: 56; Gupta & Singh, 2015: 10; Schumacker & Lomax, 2010: 76)
Root mean square error of approximation (RMSEA)	0.061	**0.056**	< 0.05 – 0.08 (Gupta & Singh, 2015: 11; Schumacker & Lomax, 2010: 76)
Standardised root mean square residual (SRMR)	0.081	**0.047**	≤ 0.08 – 0.10 (Hair et al., 2014a: 579)
Adjusted goodness-of-fit index (AGFI)	0.65	**0.84**	> 0.80 (Gupta & Singh, 2015: 10; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012)
Incremental/relative fit indices			
Normed fit index (NFI)	0.73	0.87	≥ 0.90 (Awang, 2012: 56; Hu & Bentler, 1999: 27; Malhotra & Dash, 2012; Newsom, 2018: 2; Schumacker & Lomax, 2010: 76)
Tucker Lewis index (TLI)	0.80	**0.91**	
Comparative fit index (CFI)	0.81	**0.92**	

Goodness-of-fit measures	Original model fit outcomes	Revised model fit outcomes	Acceptable fit threshold
Information-theoretic fit indices			
Akaike's information criterion (AIC)	6 795.4	**1 216.8**	Min./small (Schumacker & Lomax, 2010: 76; Wu et al., 2019: 8)
Bayesian information criterion (BIC)	7 657.3	**1 501.3**	

The results in Table 6.21 provide an overview of the model fit of the adjusted measurement model, which includes the CMIN value (1080.78), together with its degrees of freedom (*df* = 428) and probability value ($p \leq 0.001$). The CMIN value was significant and small compared to the value of the original model (6 383.40) and the CMIN/*df* ratio was 2.525 (CMIN/*df* ≤ 3; Awang, 2012: 56; Hu & Bentler, 1999: 27), which indicates a good model fit. According to these guidelines, the revised measurement model appeared to fit the data well. However, Hu and Bentler (1999: 27) advise that the CMIN value should be used with caution and other fit indices should be used to assess the model's fit.

The revised model yielded an RMSEA value of 0.056 (against the recommended threshold of between 0.05 and 0.08) and an SRMR value of 0.047 (against the recommended threshold of ≤ 0.08). The RMSEA and SRMR values were in accordance with the prescribed threshold indicative of an acceptable model fit. The AGFI significantly improved from a mediocre model fit of the original model to an adjusted model, indicating a good model fit with a value of 0.84, as against the prescribed threshold of > 0.80 (Hu & Bentler, 1999: 27). The revised measurement model furthermore yielded improved TLI (0.91) and CFI (0.92) values, against the prescribed threshold of ≥ 0.90 (Awang, 2012: 56; Hu & Bentler, 1999: 27; Schumacker & Lomax, 2010: 76). The NFI, although significantly improved from the original model fit value (0.73 to 0.87), remained slightly below the recommended threshold of ≥ 0.90 (Awang, 2012: 56). Lastly, both information-theoretic fit indices, namely AIC and BIC, improved meaningfully with the revised measurement model with values of 1 216.8 and 1 501.3, respectively, indicating good model fit. The CMIN/*df* value, RMSEA, SRMR, AGFI, TLI, CFI, AIC and BIC values therefore met the minimum requirements for a good model fit. The adjusted measurement model was considered to have satisfactory goodness-of-fit and further respecification was not required. The revised measurement model appeared to fit the data well.

6.4.2.2 Reliability and validity assessment of revised measurement model

Since the data should not be viewed in isolation, the validity and reliability of the revised measurement model were evaluated for each of the remaining constructs, as shown in Tables 6.22 and 6.23 below.

Table 6.22: Reliability and validity for the revised model – Composite reliability and AVE

Construct	Composite reliability	Average variance extracted (AVE)
Social influence	**0.780**	**0.544**
Perceived risk	**0.861**	**0.556**
Perceived customer value	**0.930**	0.439
Behavioural intention	**0.893**	**0.582**

Note: Composite reliability (≥ 0.70)
AVE (≥ 0.50)

Table 6.22 indicates the reliability and validity results of the revised measurement model. The constructs were retained because the reliability (i.e. composite reliability) for all the remaining observed variables was above the recommended threshold of 0.70 (≥ 0.70) (Hair et al., 2011: 140; Hamid et al., 2017: 2; Lin et al., 2020: 3). Moreover, the convergent reliability (AVE) for social influence, perceived risk and behavioural intention was above the prescribed 0.50 threshold (≥ 0.50). Although the convergent reliability (AVE) for perceived customer value was below the recommended threshold of 0.50 (AVE: 0.439), Pasamar, Johnston and Tanwar (2020: 785) state that an AVE value of 0.40 is acceptable if the composite reliability is higher than 0.60 – in this case, the composite reliability for perceived customer value was 0.930 and consequently the AVE is acceptable. As a result, convergent validity was achieved for each of the four remaining constructs.

The results of the discriminant validity assessment of the revised measurement model, using the HTMT criterion as proposed by Henseler et al. (2015: 121), are summarised in Table 6.23.

Table 6.23: Discriminant validity assessment of revised model: Heterotrait-monotrait (HTMT) criterion

Construct	Social influence	Perceived risk	Behavioural intention	Perceived customer value
Social influence				
Perceived risk	0.125*			
Behavioural intention	0.574*	0.138*		
Perceived customer value	0.717*	0.129*	0.849*	

Note: *Strict discriminant validity threshold (≤ 0.85)

The discriminant validity for all the remaining observed variables fell within the stringent recommended validity threshold of below 0.85 (Henseler et al., 2015: 121), as presented in Table 6.23. Compared to the original measurement model, where a lack of discriminant validity was detected, significant variances in the residual constructs were observed in the revised measurement model.

Considering the goodness-of-fit assessment reported in Table 6.21, the convergent reliability results reported in Table 6.22, as well as the discriminant validity assessment results reported in Table 6.23, the revised measurement model (as presented in Figure 6.3 above) was accepted.

The CFA results discussed in section 6.4 therefore provide supporting evidence for empirical research objective 3: to assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention.

Further statistical analyses reported below were conducted based on the revised measurement model presented in Figure 6.3 above. The descriptive statistics of the revised measurement model are reported in the subsequent section.

6.5 ASSUMPTION OF NORMALITY: CONSTRUCT DESCRIPTIVE STATISTICS OF THE REVISED MEASUREMENT MODEL

Construct descriptive statistics related to the four constructs derived from observed scores were analysed to explore the suitability of the items measuring the latent variables. In assessing the construct descriptive statistics, multivariate measures or summated scales, for which several variables are joined in a composite measure to represent a concept, were used (Hair et al., 2014b: 8). In this case, the separate variables were summed and their total or average score was used in the analysis.

The mean, standard deviation, skewness and kurtosis of the remaining four constructs, namely social influence, perceived risk, perceived customer value and behavioural intentions, are reported in Table 6.24 and further investigated below. These statistics report the extent to which consumers measured on each of the constructs and do not infer any relationship regarding the dependent variable.

Table 6.24: Construct descriptives: Mean, standard deviation, skewness and kurtosis of social influence, perceived risk, perceived customer value and behavioural intention

Construct	Scale items measuring construct[#]	Mean	95% confidence interval for mean		Std dev.	Skewness	Kurtosis
			Lower bound	Upper bound			
SI	SI1 – SI3	3.82	3.75	3.90	0.816	-0.69	0.61
PR	PR1; PR5; PR6; PR7; PR8	3.12	3.03	3.20	0.969	-0.18	-0.62
PCV	PE1; PE3; EE2; EE3; FC2; HM1; HA1; HA3; PV1; PV2; PV4; LSC4; LSC8; ATT1; ATT2; ATT3; ATT5	4.19	4.14	4.23	0.550	-0.56	0.22
BI	BI1 – BI6	4.24	4.18	4.29	0.624	-0.64	0.19

Key: Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Behavioural intention (BI)

Notes: [#] Refer to Annexure C for a complete list of statements used in the research instrument.

For the revised measurement model discussed in section 6.4.2 and presented in Figure 6.3, the overall mean, standard deviation, skewness and kurtosis of the constructs are presented. All constructs were measured on a 5-point Likert scale, with 1 = strongly disagree and 5 = strongly agree, over a midpoint of 3 (neither disagree nor agree).

The mean scores were interpreted as follows: 1 to 1.50 indicates that respondents strongly disagreed; mean scores between 1.51 and 2.50 imply that respondents disagreed; 2.51 to 3.50 indicates that respondents were unsure or felt impartial; 3.51 to 4.50 indicates that respondents agreed; and a mean score of above 4.5 inferred that respondents strongly agreed with the statement. A standard deviation of more than 1 (≥ 1) was considered a substantial dispersion of responses in the dataset. Data were considered normally distributed if the skewness and kurtosis values were in the range of -2 and +2 (Barry et al., 2011: 103).

6.5.1 SOCIAL INFLUENCE

Scale items SI1, SI2 and SI3 (Q5.3, Q5.12 and Q5.26) were summated to calculate the descriptive statistics of the social influence construct. As can be seen from Table 6.24 above, the average mean score for social influence was 3.82, indicating that respondents typically agreed that their decisions were influenced by people who were important to them, whose opinions they valued and who recommended using same-day delivery apps. The results are in line with those of Malik et al. (2017: 109), who indicates that consumers' decisions are highly influenced and shaped by the suggestions, comments, reviews and posts of significant others and other users. The standard

deviation of the construct was 0.816, indicating that the agreement between the responses about these statements measuring social influence was homogeneous. Additionally, it can be concluded that the dataset was normally distributed as the skewness value is between -2 and +2 (-0.69) and the distribution is slightly leptokurtic, with a kurtosis value of > 0 (0.61).

The descriptive results for the social influence construct are presented univariately in Figure 6.4, which indicates normal distribution.

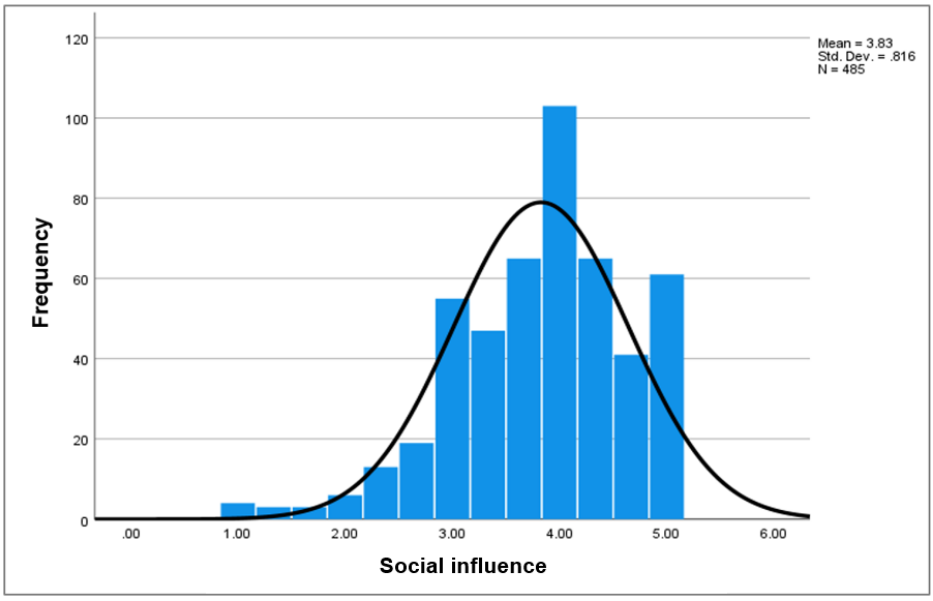

Figure 6.4: Univariate descriptive results for social influence

6.5.2 PERCEIVED RISK

Scale items PR1, PR5, PR6, PR7 and PR8 (Q5.15, Q5.35, Q5.51, Q5.58 and Q5.60) were summated to calculate the descriptive statistics of the perceived risk construct. The mean and standard deviation scores for the perceived risk construct, as well as the skewness and kurtosis, are depicted in Table 6.24 above.

The average mean score for the perceived risk construct was 3.12, indicating that respondents, on average, were impartial about the statements representing perceived risk. As discussed in section 6.3.1.9 above, the neutrality towards perceived risk could be attributed to respondents feeling exposed to risk when transacting on same-day delivery apps due to the infancy of certain of these apps in the South African market (at the time the study was conducted). Belanche et al. (2020: 6) and Kaushik et al. (2020: 12) state that users' concern for privacy and security on mobile shopping apps impedes the adoption of online or mobile shopping apps. Respondents were

doubtful about the outcome of their decision in purchasing online and the risks involved in doing so (Pauzi et al., 2017: 5).

The standard deviation was 0.969, representing acceptable variation in respondents' level of agreement regarding the statements measuring perceived risk. It can be inferred that respondents felt exposed to risk when transacting on same-day delivery apps and felt that, compared to other methods of purchasing, same-day delivery apps were riskier and posed many uncertainties. The dataset was normally distributed as the skewness value was between -2 and +2 (-0.18), with a slight leptokurtic curve (0.62).

Figure 6.5 presents the univariate descriptive statistics of the perceived risk construct.

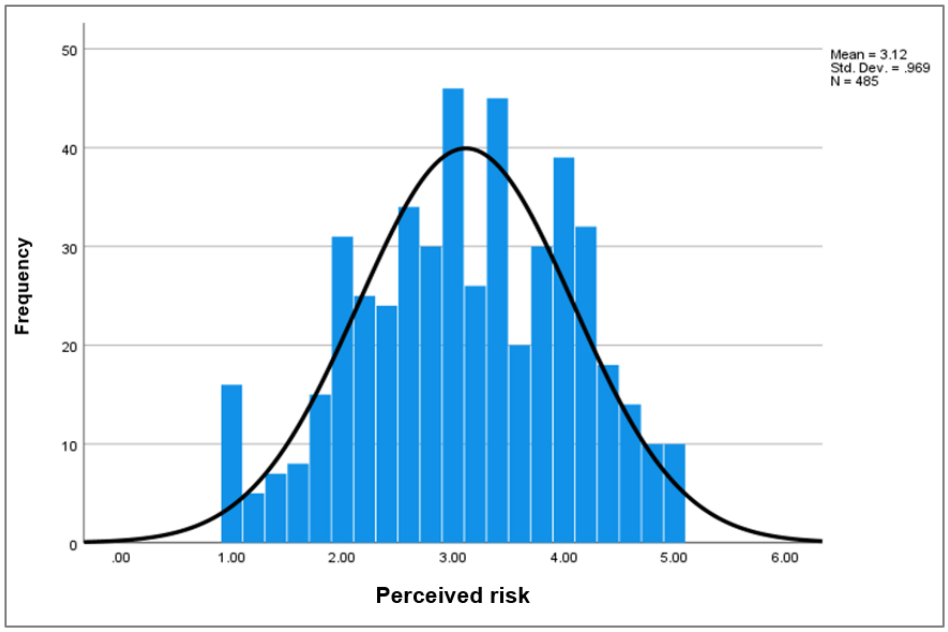

Figure 6.5: Univariate descriptive results for perceived risk

6.5.3 PERCEIVED CUSTOMER VALUE

The newly emerged construct of perceived customer value was derived by summating 17 scale items as listed in Table 6.24. The average mean score for the newly established construct was 4.19, suggesting that respondents, on average, agreed that the benefits received from using same-day delivery apps outweighed the perceived losses. The standard deviation of the construct was 0.550, implying that the agreement between respondents regarding the perceived value derived from same-day delivery apps was homogeneous across the dataset.

Chang and Dibb (2012: 256) as well as Jansri (2018: 1) argue that perceived customer values are strong predictors of behaviour because consumers decide to purchase a product after considering multiple consumption values, such as enjoyment, quality, value-for-money and their trade-offs. For purposes of this study, the trade-off between the sacrifices made to continuously use same-day delivery apps outweighs the benefits and satisfaction received from using these particular apps.

From the results discussed above, it can be presumed that consumers generally agree that same-day delivery apps increase their productivity, permitting them to do things that are more important to them, are easy to use and compatible with other smart devices they use, are fun, a good idea or better to use and are cost-effective. Therefore, it can be deduced that the benefits and satisfaction derived from using same-day delivery apps outweigh the sacrifices made by consumers when using same-day delivery apps.

Moreover, the skewness value (-0.56) indicates that the data were normally distributed, and a near-perfect or mesokurtic distribution of results is inclined by the kurtosis value of 0.22. The univariate descriptive statistics of the newly established perceived customer value construct are graphically portrayed in Figure 6.6. The data were normally distributed.

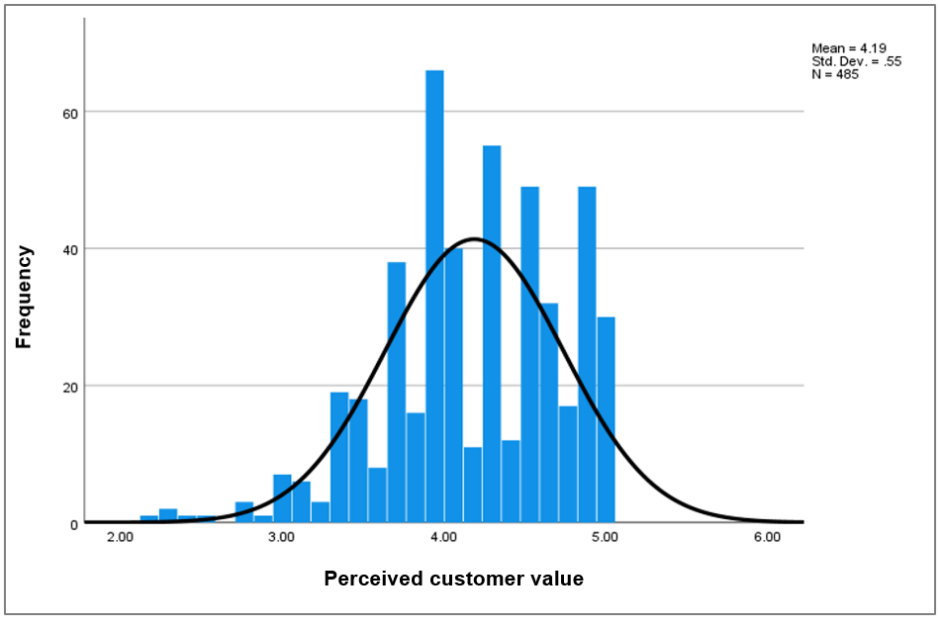

Figure 6.6: Univariate descriptive results for perceived customer value

6.5.4 BEHAVIOURAL INTENTION

Scale items BI1 to BI6 (Q6.1 to Q6.6) were summated to calculate the descriptive statistics of the dependent construct (behavioural intention). The average mean and standard deviation values,

as well as the skewness and kurtosis analysis of the dependent variable, are shown in Table 6.24 above. The average mean score for behavioural intention was 4.24, signifying that respondents, on average, agreed with the statements representing behavioural intention. A slight variation in respondents' level of agreement is evident, with a relatively small standard deviation score of 0.624. As a result, it can be assumed that respondents typically agreed that they intended to use or continue using same-day delivery apps in the future. These results are in line with the literature stating that an individual's intention to perform a specific behaviour is the best predictor of whether the individual will perform that given behaviour (Ajzen, 1991 in Kendrick, 2011). Respondents were therefore likely to use same-day delivery apps as their intention to do so was equitably agreeable.

The dataset for the behavioural intention construct was furthermore normally distributed with a skewness value between -2 and +2 (-0.64). The kurtosis value (0.19) indicates a near-perfect or mesokurtic distribution. Figure 6.7 illustrates the univariate descriptive statistics of the behavioural intention construct, which indicates a normal distribution of results.

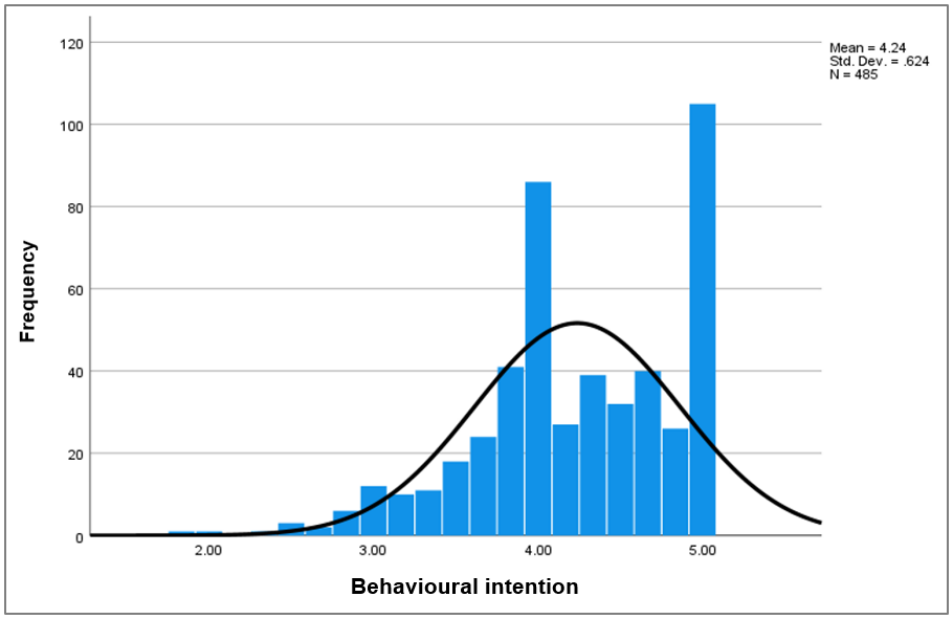

Figure 6.7: Univariate descriptive results for behavioural intention

From the results discussed above, it can be concluded that social influence, perceived risk and perceived customer value are relevant to a sample of South African consumers because on average the majority of respondents agreed with the statements representing each of these constructs. Additionally, the assessment of normality indicated satisfactory skewness and kurtosis values; therefore, the assumption of normality for the revised measurement model was met. Accordingly, it was considered appropriate to proceed with inferential and multivariate statistical

analyses on the revised measurement model, including SEM, correlation analysis, moderation analysis and test for group mean differences.

6.6 INFERENTIAL AND MULTIVARIATE STATISTICAL ANALYSES

Inferential statistics are used by researchers to determine whether an expected pattern designated by the theory and hypotheses is found in the observations (Frankfort-Nachmias et al., 2015: 305). Multivariate analyses are conducted where two or more measurements of each element are observed, and the variables are analysed simultaneously (Malhotra, 2019: 423). Inferential and multivariate statistics were used to draw inferences or conclusions about the population from the sampled data.

Inferential statistical analysis entailed the following four steps:

1) *Correlation analysis* was conducted to examine the direction and strength between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers (empirical research objective 4).
2) *Structural equation modelling (SEM)* was conducted to evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model (empirical research objective 5).
3) *Moderation analysis* was conducted to assess whether the interaction effects between the independent variables (social influence, perceived risk and perceived customer value) on the dependent variable (behavioural intention) were conditional upon their disposition in terms of generational cohort and gender (moderating variables) (empirical research objective 6).
4) *Tests for significant group mean differences* were examined to determine whether consumers from various demographic groups (generational cohort and gender) differ significantly regarding the variables: social influence, perceived risk, perceived customer value (independent variables) and behavioural intention (dependent variable) (empirical research objective 7).

6.6.1 CORRELATIONS BETWEEN THE MEASUREMENT MODEL'S INDEPENDENT VARIABLES AND BEHAVIOURAL INTENTION

Correlational analysis is used to assess the strength and the direction of the linear association between two different variables (Frankford-Nachmias et al., 2015: 338; Venter & Van Zyl, 2017:

173). Pearson's product-moment correlation coefficient (symbolised as *r*) is typically assessed when the strength of association between two continuous metric (interval or ratio scaled) variables is determined, as in the case of the research study. Therefore, Pearson's product-moment correlation coefficient was analysed to address empirical research objective 4: to examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers.

The Pearson product-moment correlation coefficient (*r*) represents the linear association between two metric variables and serves as the basis for many multivariate calculations (Kirsten, 2019: 672). It ranges from -1 and +1, with 0 representing no linear association between the variables, -1 representing a perfect negative correlation and +1 indicating a perfect positive correlation (Venter & Van Zyl, 2017: 173). The higher the absolute value of the coefficient, the stronger the linear relationship. A strong correlation does not imply a cause-effect relationship, but signifies the strength and direction of the linear association between the two variables (Kirsten, 2019: 672).

Table 6.25 reports Pearson's product-moment correlation coefficient results between the independent variables of the revised measurement model and the dependent variable (behavioural intention). In line with Cohen's guidelines (1988), a Pearson's *r* of between 0.10 and 0.29 ($r \geq 0.10$ and ≤ 0.29) was regarded as indicative of a small practical effect size, $r \geq 0.30$ and < 0.50 represented a medium practical effect and $r \geq 0.50$ represented a large practical effect.

Table 6.25: Pearson's product-moment correlation coefficient

		Social influence	**Perceived risk**	**Perceived customer value**	**Behavioural intention**
Social influence	Pearson correlation	--			
	Sig. (2-tailed)				
	n	485			
Perceived risk	Pearson correlation	0.102*	--		
	Sig. (2-tailed)	0.025			
	n	485	485		
Perceived customer value	Pearson correlation	0.615**	-0.108*	--	
	Sig. (2-tailed)	< 0.001	0.018		
	n	485	485	485	
Behavioural intention	Pearson correlation	**0.482****	**-0.115***	**0.773****	--
	Sig. (2-tailed)	< 0.001	0.011	< 0.001	
	n	485	485	485	485

Note: *Correlation is significant at the 0.05 level (2-tailed)

**Correlation is significant at the 0.001 level (2-tailed)

The results of the Pearson correlation analysis, reported in Table 6.25, revealed a significant ($p \leq 0.01$) and positive ($r = 0.482$) association between social influence and behavioural intention. In line with Cohen's guidelines, the association between social influence and behavioural intention has a medium practical effect ($r \geq 0.30$ and < 0.50).

The scatterplot in Figure 6.8 indicates the association between social influence and behavioural intention. Higher levels of social influence are associated with higher levels of behavioural intention. Individuals are highly influenced and shaped by the suggestions, comments, reviews and posts of significant others and other users, and tend to choose technology based on personal preferences (Naqvi, Jiang, Miao & Naqvi, 2020: 4; Malik et al., 2017: 107). Therefore, the more favourable reviews and recommendations an individual's social network provide about a shopping app, the higher that individual's intention to continue using the specific app will be.

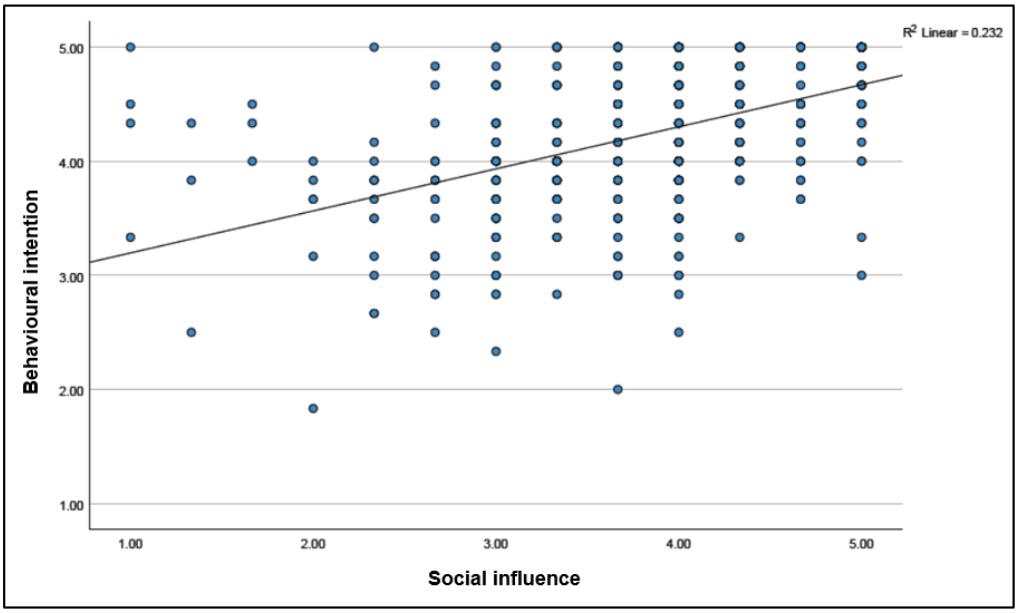

Figure 6.8: Scatterplot – Correlation between social influence and behavioural intention

The Pearson correlation analysis (see Table 6.25) further revealed a significant ($p \leq 0.05$) but very low negative correlation ($r = -0.115$) between perceived risk and behavioural intention, with a small practical effect ($r \leq 0.29$). Accordingly, if the risks associated with using same-day delivery apps are perceived to be too high and pose too many uncertainties, individuals will have lower intentions to use same-day delivery apps. On the contrary, if same-day delivery apps pose little risk to users, the users will present with heightened intentions to use these apps. Many researchers have acknowledged that one of the main factors discouraging individuals from using online platforms or mobile shopping apps is their concern about privacy and security (i.e. risk factors) (e.g. Chopdar

et al., 2018: 3; Hubert et al., 2017: 181; Kaushik et al., 2020: 12). The correlation effect is represented by a scatterplot in Figure 6.9.

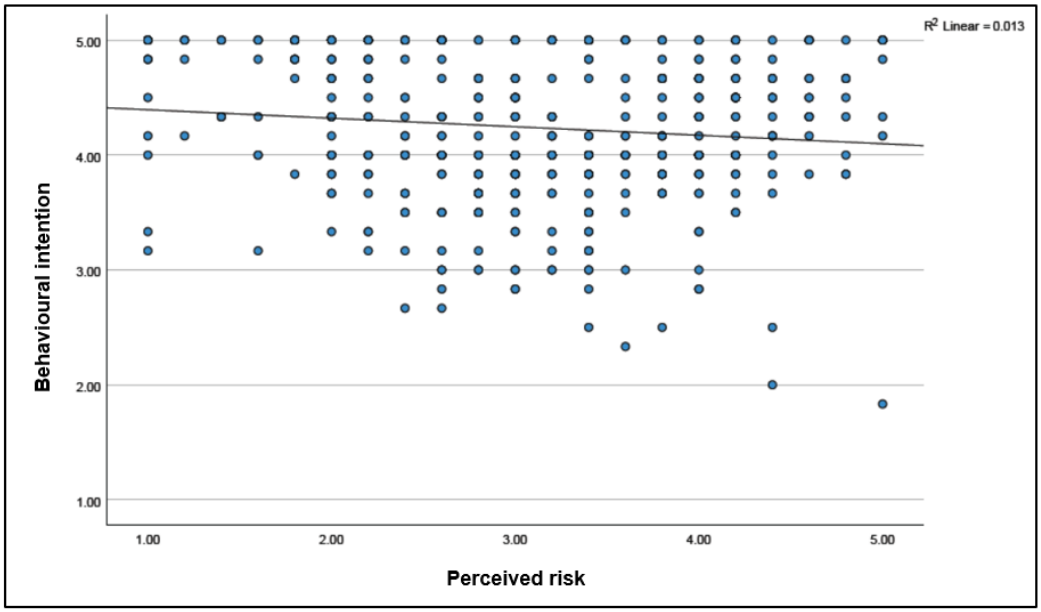

Figure 6.9: Scatterplot – Correlation between perceived risk and behavioural intention

Lastly, the results of the Pearson correlation analysis show a significant ($p \leq 0.05$) and high positive correlation ($r = 0.773$) between perceived customer value and behavioural intention (see Table 6.25). Based on Cohen's guidelines, the association between perceived customer value and behavioural intention is considered large in practical effect ($r \geq 0.50$). A high level of perceived customer value is therefore associated with a high level of behavioural intention, as shown in the scatterplot below (Figure 6.10). The literature supports the correlation between perceived customer value and behavioural intention (e.g. Khan & Kadir, 2011: 4094; Mahendar, 2017: 100; Zhang, Liu, Zhang & Pang, 2021: 29). Perceived value simultaneously integrates customers' perception of the benefits received and the sacrifices involved in using the technology (Jen, Tu & Lu, 2011: 326), and is therefore highly associated with usage intention (Mahendar, 2017: 89).

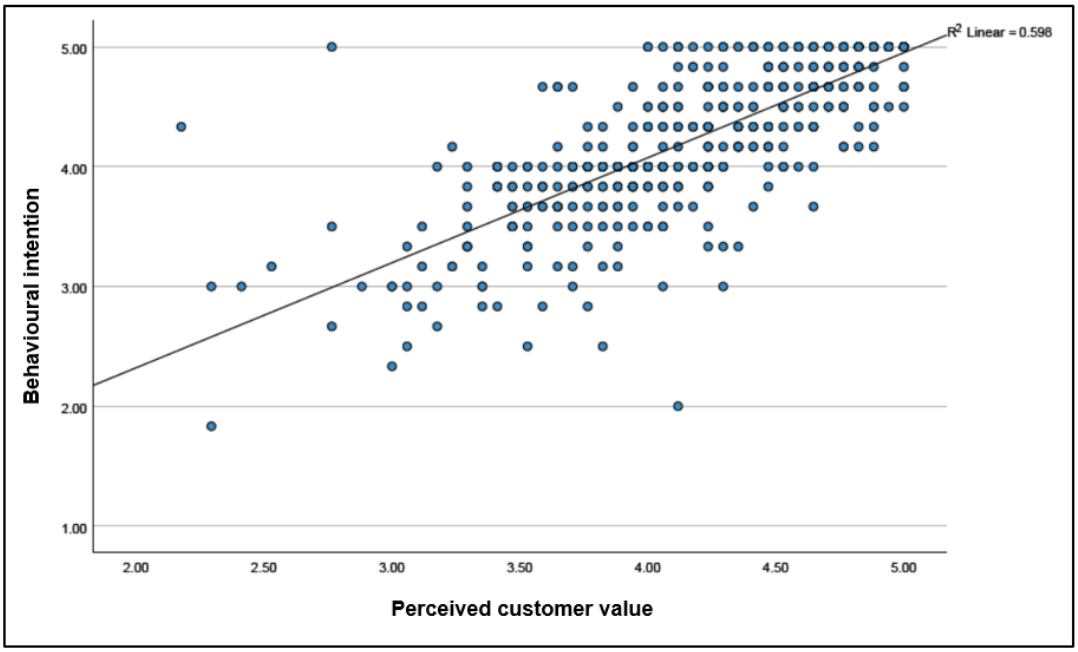

Figure 6.10: Scatterplot – Correlation between perceived customer value and behavioural intention

The results observed regarding Pearson's product-moment correlation coefficients provide supporting evidence for empirical research objective 4: to examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers. Significant correlations were observed between all independent variables (social influence, perceived risk and perceived customer value) and behavioural intention. Positive correlations were noted between social influence as well as perceived customer value and behavioural intention. A negative correlation was observed between perceived risk and behavioural intention.

The assumption of normality was achieved with acceptable skewness and kurtosis values (refer to Table 6.24). The assumption of homoscedasticity and linearity was also evident in the scatterplots presented in Figures 6.8 to 6.10.

Based on the results of the correlation analysis, SEM could be conducted, which further explored the significance and variance explained by the constructs under investigation. The next step in the inferential and multivariate statistical analysis process therefore involved conducting SEM.

6.6.2 STRUCTURAL MODEL FOR CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

SEM is a multivariate procedure that combines regression and factor analysis and can be described as a theory-driven approach to data analysis for estimating a series of dependent relationships between a set of concepts or constructs represented by multiple measured variables and incorporated into a unified model (Malhotra, 2019: 666; Potgieter, 2012: 224). SEM is considered an analytical process involving model conceptualisation, parameter identification and estimates, data-model fit assessment and potential model specifications (Kirsten, 2019: 679). It is therefore used as an inference statistical method which assesses both the quality of measurement (the measurement model) and the strength of the directional paths between latent variables referred to as the structural model by combining aspects of factor analysis and multiple regression (Hair et al., 2014a: 546).

SEM required the proposed conceptual model (refer to Chapter 4, Figure 4.1) to be broken up into a measurement model and a structural model. The measurement model depicts how different variables come together to represent constructs, and the structural model portrays each construct's association with the other (Van Niekerk, 2020: 256). As the initial conceptual model was discredited as shown in section 6.4.1, due to the lack of discriminant validity, unsatisfactory convergent validity and unacceptable model fit indices, a revised measurement model emerged from the data (see Figure 6.3). For purposes of the research study, the main aim in conducting SEM was to determine whether the sample data supported the revised empirically manifested measurement model (Tabachnick & Fidell, 2019). Accordingly, the structural model was determined based on the revised measurement model as discussed in section 6.4.1 and illustrated in Figure 6.3.

A structural equation model, generated through AMOS (version 27), was used to test the relationships between the empirically manifested independent variables (social influence, perceived risk, perceived customer value) and the dependent variable (behavioural intention). AMOS excels at uncovering complex relationships and hidden structures within data by employing a powerful covariance-based approach that analyses the shared variances among variables to tease out their interconnectedness and causal pathways. As previously discussed, a good-fitting model is accepted if the value of the CMIN/*df* is ≤ 3 (Hu & Bentler, 1999: 27), and the GFI, TLI, NFI and CFI are ≥ 0.90 (Awang, 2012: 56; Schumacker & Lomax, 2010: 76). Moreover, an adequate-fitting model is accepted if the value of the RMSEA is between 0.05 and 0.08, the SRMR is ≤ 0.08, but not more than 0.10 and the AGFI is > 0.80 (Gupta & Singh, 2015: 11; Hair et al.,

2014a: 579; Schumacker & Lomax, 2010: 76). Apart from the GFI and NFI, which fell below the acceptable threshold of ≥ 0.90, the model fit indices for the revised measurement model (as shown in Table 6.21) fell within the prescribed acceptable ranges: CMIN/*df* = 2.525; RMSEA = 0.056; SRMR = 0.047; AGFI = 0.84; TLI = 0.91; CFI = 0.92. The information-theoretic fit indices (AIC and BIC) were also considered small (AIC = 1 216.8; BIC = 1 501.3) compared to the original model (Schumacker & Lomax, 2010: 76; Wu et al., 2019: 8). The revised measurement model presented in Figure 6.3 therefore fit the data well.

The revised measurement model was also subjected to reliability and validity assessments. Convergent validity was achieved with composite reliability values of ≥ 0.70 and acceptable AVE scores (≥ 0.50) (see Table 6.22). Discriminant validity was assessed by means of the HTMT criterion, and all remaining observed variables (social influence, perceived risk, perceived customer value and behavioural intention) fell within the stringent recommended threshold of below 0.85 (see Table 6.22). Significant variances in the residual constructs were observed in the revised model. Based on the assessment of the revised measurement model, the model was considered to have satisfactory goodness-of-fit indices and acceptable convergent reliability and discriminant validity. The revised measurement model was accepted, and further analysis could be conducted on the revised model.

The next step, which is the focus of this section, entailed drawing a path structure indicating the directional influences that best predict behavioural intention. Following the selection of the best-fit model, it was necessary to determine how well the independent variables (social influence, perceived risk, perceived customer value) were predicted, which was achieved by determining the statistical significance of the standardised regression weights ($p \leq 0.05$) and establishing whether the parameter estimates were in the prescribed directions (Hair et al., 2014a: 570). SEM was therefore assessed to achieve empirical research objective 5: to evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model.

A graphical representation of the complete structural model is provided in Figure 6.11. The parameters shown are the path coefficients (standardised regression weights) that represent the relationships between the proposed variables and the outcome variables. The Likert scale items all showed significant positive factor loadings, with standardised coefficients ranging from 0.605 to 0.842. The squared multiple correlation (R^2), standardised regression weights as well as the correlation estimates, per Likert scale item, can be found in Annexure I.

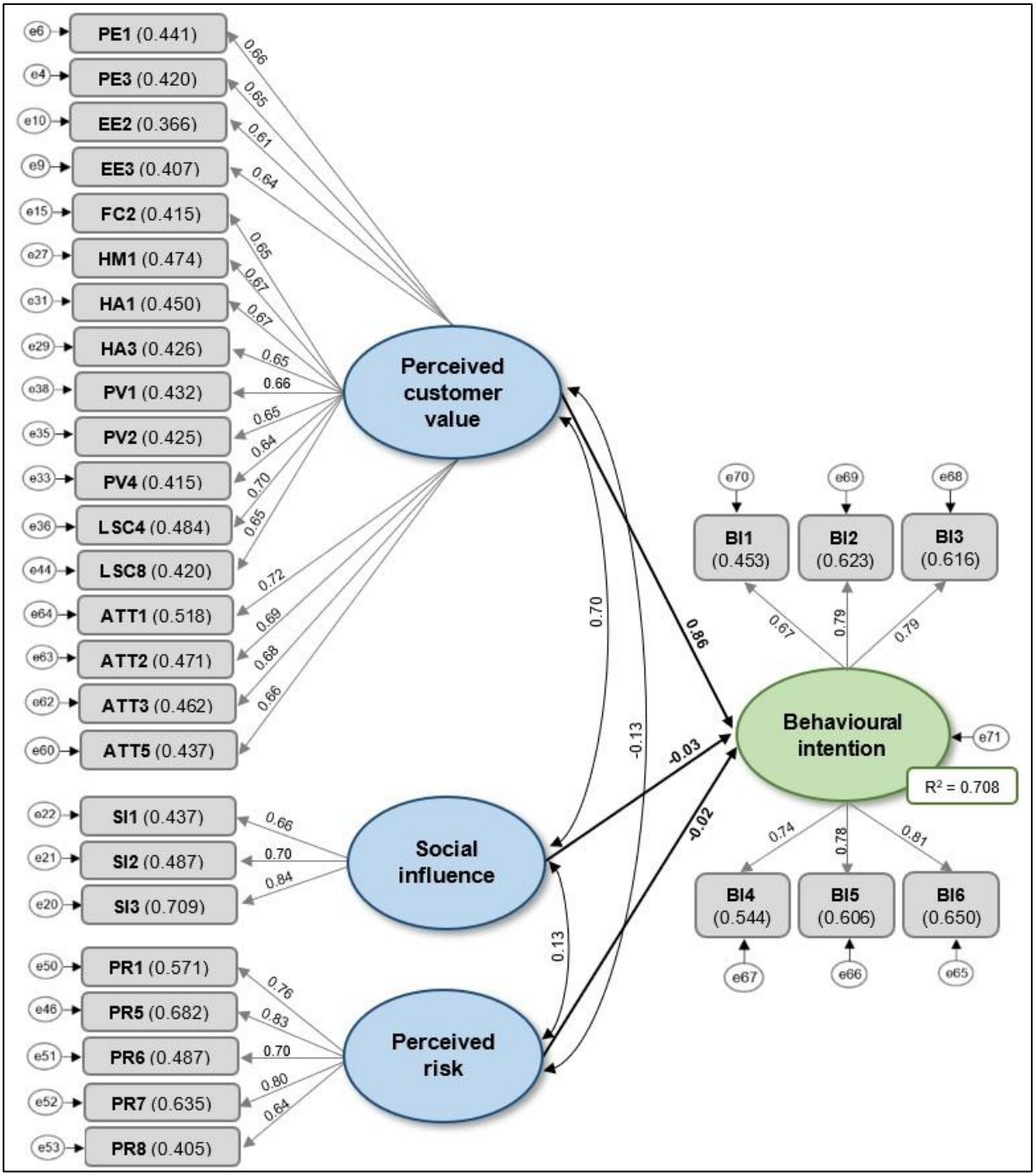

Figure 6.11: Structural model with R^2, standardised regression weights and correlation estimates

Table 6.26 summarises the structural model estimates, including the parameter estimates, *t*-statistics and *p*-value for each of the hypothesised relationships.

Table 6.26: Structural model estimates for the revised model

Structural paths	Standardised coefficient (*β*)	*t*-value	*p*-value	R^2
H1: Social influence → Behavioural intention	-0.026	-0.452	0.651	0.708
H2: Perceived risk → Behavioural intention	-0.020	-0.546	0.585	
H3: Perceived customer value → Behavioural intention	0.857	11.256	**≤ 0.001**	
Model fit				
CMIN/*df* = 2.525; RMSEA = 0.056; SRMR = 0.047; AGFI = 0.84; TLI = 0.91; CFI = 0.92; AIC = 1 216.8; BIC = 1 501.3				

The model fit assessment revealed that the model explains an estimated 70.8% (R^2 = 0.708) of the variance in behavioural intention. In terms of relative importance, behavioural intention is mostly explained by perceived customer value (85.7%; β = 0.857). The statistically significant correlation was also observed in Pearson's correlation coefficient discussed in section 6.6.1 (r = 0.773; $p \leq 0.01$). The variance could be attributed to consumers' overall assessment of products and/or services based on the varied benefits and sacrifices (Chahal & Kumari, 2012: 168). It is natural for individuals to weigh up the benefits derived from using a product and/or service against the sacrifices they must make in order to use it. In this case, consumers considered the productivity derived from using the apps (which includes scale items PE1, PE3, FC2 and LSC8), the ease of use (scale items EE2 and EE3), fun, excitement and smart way of shopping (scale items HM1, HA1, HA3, LSC4, ATT1, ATT2, ATT3 and ATT5) and their cost-effectiveness (scale items PV1, PV2 and PV4) as the advantages of using same-day delivery apps (refer to Addendum C for a complete list of scale items used in the research instrument). These results are in line with Chang and Dibb (2012: 256) as well as Jansri (2018: 1), who maintain that perceived customer value is strongly correlated with price, quality, sacrifice and satisfaction and are thus useful predictors of behaviour.

SEM was used to determine empirical research objective 5: to evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model. A structural model was developed to evaluate the interrelationships between the empirically manifested variables. The structural model was based on the statistical interrelationships between social influence, perceived risk, perceived customer value and behavioural intention. The revised measurement model presented in Figure 6.3 indicated a good overall fit, with acceptable reliability and validity. The structural model fit assessment revealed that the model explains an estimated 70.8% (R^2 = 0.708) of the variance in behavioural intention. Parameter estimates and *t*-statistic values revealed a statistically insignificant relationship between social influence as well as perceived risk and behavioural intention (refer to Table 6.26). A significant positive relationship between perceived customer value and behavioural intention is evident (β = 0.857; t = 11.256;

$p \leq 0.01$). Lastly, the results revealed that behavioural intention is mostly explained by perceived customer value ($\beta = 0.857$). A reliable and valid structural model for consumers' behavioural intention was therefore developed.

6.6.2.1 Hypotheses and revised conceptual model

Given the outcomes of SEM discussed above, the following hypotheses are stated:

H_a1: There is a significant relationship between social influence and consumers' behavioural intention to continue using same-day delivery apps.

H_a2: There is a significant and negative relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps.

H_a3: There is a significant relationship between perceived customer value and consumers' behavioural intention to continue using same-day delivery apps.

H_a4: Generational cohort and gender significantly moderate the relationship between the independent variables and behavioural intention to continue using same-day delivery apps.

The revised conceptual model indicating three central independent constructs that likely predict consumers' behavioural intention, namely social influence, perceived risk and perceived customer value, is presented in Figure 6.12. This model is based on the outcomes of the structural model discussed above and presented in Figure 6.11.

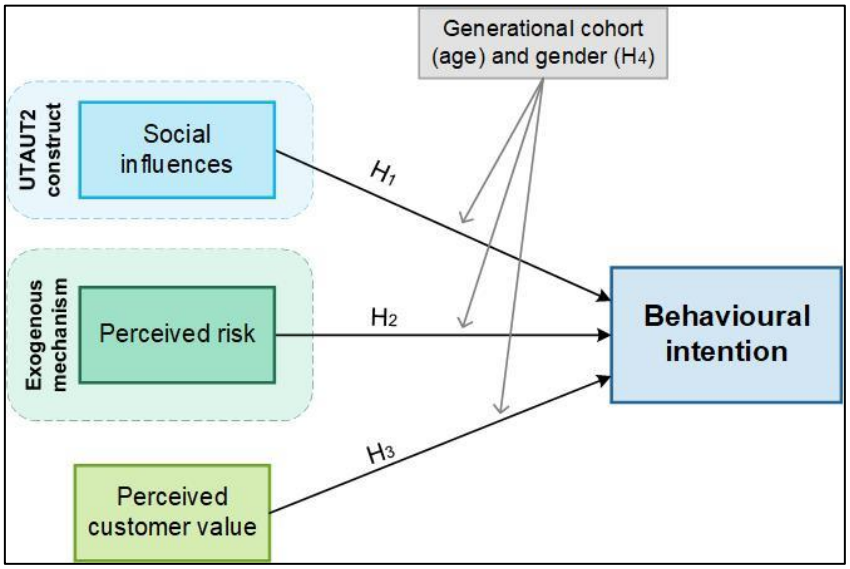

Figure 6.12: A revised conceptual model based on the outcomes of SEM

Source: Author's own compilation

The revised conceptual model is based on the statistical interrelationships, evident in the structural model, between social influence, perceived risk, perceived customer value and behavioural intention. The hypotheses, as stated above and illustrated in Figure 6.12, will be analysed in the next section.

6.6.2.2 Hypothesis testing

Hypothesis testing is used to confirm if the estimated regression coefficients (*β*) bear any significance in a regression model. In the case of the research study, the *t*-statistic was examined to ensure the validity of the hypothesised relationships and test the null hypothesis (Hair, Black, Babin & Anderson, 2010: 677). The regression coefficient (*β*) should exceed 0.50 to be regarded as good, and the *t*-statistic value should exceed 1.96 with a probability value of ≤ 0.05 (Hair et al., 2010: 677; Malhotra, 2010: 705).

The hypothesis (H_a1) tests if social influence significantly influences consumers' behavioural intention to continue using same-day delivery apps. When assessing the results reported in Table 6.26, it is evident that the relationship between social influence and behavioural intention was negative and not significant (β = -0.026; t = -0.452; p = 0.651). Additionally, H_a2 tests whether perceived risk significantly and negatively influences consumers' behavioural intention to continue using same-day delivery apps. It is evident from Table 6.26 above that perceived risk negatively (β = -0.020) impacts behavioural intention, but the results are statistically insignificant (t = -0.546; p = 0.585). The standardised regression coefficients and *t*-statistic for both social influence and perceived risk were below the recommended threshold of ≥ 0.50 and ≥ 1.96, respectively, and the probability value for both variables was non-significant at the 5% level of confidence ($p \geq 0.05$). Consequently, H_a1 and H_a2 are not supported and the null hypothesis is accepted for both hypotheses:

- **$H_0$1:** There is no significant relationship between social influence and consumers' behavioural intention to continue using same-day delivery apps.
- **$H_0$2:** There is no significant relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps.

A third latent variable emerged from the CFA assessment discussed in section 6.4.1. As a result, H_a3 (*There is a significant relationship between perceived customer value and consumers' behavioural intention to continue using same-day delivery apps)* was included in the study as research suggested that consumer values are useful predictors of behavioural intention because a consumer's decision to purchase products and/or services, or in this case use mobile

technology, is susceptible to multiple consumption values, such as the price, quality, gratification as well as their trade-offs or losses (Chang & Dibb, 2012: 256; Jansri, 2018: 1). The data from the research study, as indicated in Table 6.26, show a positive and statistically significant (β = 0.857; t = 11.256; $p \leq 0.001$) relationship between perceived customer value and behavioural intention, thereby supporting H_a3 and rejecting the null hypothesis.

A view of the model with accepted relationships indicated in red is presented in Figure 6.13. H_a1 and H_a2 were not supported, but H_a3 was. The interaction effect (H_a4) will be addressed in the following section.

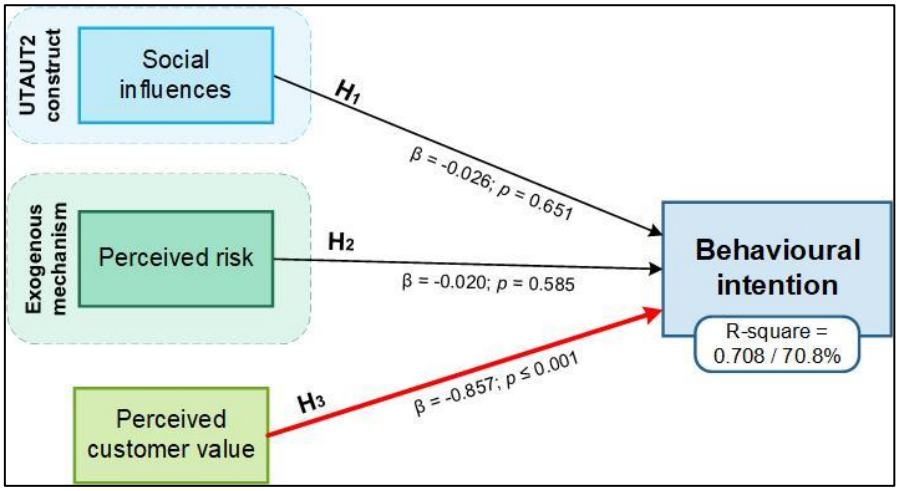

Figure 6.13: Model with accepted relationship (hypothesis) indicated in red
Source: Author's own compilation

The following section covers the results of the moderation analyses conducted to address empirical research objective 6.

6.6.3 THE INTERACTION EFFECT BETWEEN THE INDEPENDENT VARIABLES AND DEPENDENT VARIABLE AND TWO DEMOGRAPHIC CONDITIONS (MODERATION ANALYSIS)

On the grounds of the best fit structural equation model shown in Figure 6.11, moderated regression analysis was performed using Hayes' Process Macro for SPSS (2018), version 3.5.3, to determine the interaction effects between the independent variables (social influence, perceived risk and perceived customer value) and the dependent variable (behavioural intention), and two demographic conditions (moderators), namely generational cohort and gender (empirical research objective 6). The purpose was to determine whether the direct influence of the independent

variables on the dependent variable is altered or changed because of a third variable, or moderator.

A moderator may be described as any variable that influences the strength and/or direction of the relationship between an independent and dependent variable (Kirsten, 2019: 844). In Chapter 4, section 4.2.13.4, hypotheses derived from theory were stated where generational cohort and gender may serve as moderating variables. Given the outcomes of the initial CFA assessment of the proposed conceptual model presented in Chapter 4 (Figure 4.1), a revised measurement model was developed that fit the data more adequately. By implication, various hypotheses stated in Chapter 4 could not be confirmed empirically (refer to section 6.4.1 above). As a result, H_a4 was stated to empirically assess the interaction effect of generational cohort and gender on the independent variables of the revised model and behavioural intention (H_a4: *Generational cohort and gender significantly moderate the relationship between the independent variables and behavioural intention to continue using same-day delivery apps*).

The next step in the inferential and multivariate statistical analysis process was to determine whether the relationship between the independent variables of the revised empirically manifested model (social influence, perceived risk and perceived customer value) and the dependent variable (behavioural intention) was conditional upon consumers' generational cohort and gender. The proposed moderating interaction between the independent and dependent variables is depicted in Figure 6.12 above.

Regression-based moderation analysis was conducted to examine (1) the interaction effects between social influence, perceived risk as well as perceived customer value (independent variables) and behavioural intention (dependent variable) and consumers' disposition in terms of *gender* (discussed in section 6.6.3.1 below) and (2) the interaction effects between social influence, perceived risk as well as perceived customer value (independent variables) and behavioural intention (dependent variable) and consumers' disposition in terms of the *generational cohort (age group)* (discussed in section 6.6.3.2 below). The aim of the moderation analysis was to determine whether the significant pathways that were detected in SEM were conditional upon gender and generational cohort.

6.6.3.1 The moderating effect of gender on the relationship between the independent variables and behavioural intention

In order to analyse the three models exploring the effects of gender on the interrelationship between social influence (model 1), perceived risk (model 2) as well as perceived customer value (model 3) and behavioural intention, a three-step process was followed. To begin with, the initial (unmoderated) equation representing the extent to which Y (dependent variable) is predicted by X (independent variable) was estimated. Thereafter, the determination of the moderated relationship was assessed by considering the change in the coefficient of determination (R^2). The existence of a significant moderating effect would be confirmed if the R^2 change was statistically significant ($p \leq 0.05$), considering the regression coefficient (XW). Lastly, any significant moderation effects identified in the analysis were probed by means of Johnson-Neyman intervals and a simple slope analysis.

The following hypothesised moderation models, regarding the interaction effect of gender, were tested and the results are reported in Table 6.27 below:

- **Model 1** tested whether the effect of *social influence* on behavioural intention was conditional upon a consumer's gender.
- **Model 2** tested whether the effect of *perceived risk* on behavioural intention was conditional upon a consumer's gender.
- **Model 3** tested whether the effect of *perceived customer value* on behavioural intention was conditional upon a consumer's gender.

The interaction effect of gender on the relationship between the independent variables (social influence, perceived risk and perceived customer value) and behavioural intention is reported in Table 6.27.

Table 6.27: Interaction effect of gender on the relationship between the independent variables (social influence, perceived risk and perceived customer value) and dependent variable (behavioural intention)

								Model summary				
Model		**Unstandardised coefficient (*b*)**	**SE**	***t***	***p***	**LLCI**	**ULCI**	**R^2**	**$R^2\Delta$**	**F**	**FΔ (*p*)**	***p***
Model 1: SI → BI (Gender)	Constant	2.830	0.140	20.167	**<0.001*** **	2.554	3.105	0.233	0.000	48.363	0.018 (0,894)	**<0.001*** **
	Social influence (X)	0.366	0.036	10.200	**<0.001*** **	0.295	0.436					
	Gender (W)	-0.008	0.270	-0.030	0.976	-0.539	0.523					
	Interaction effect (X × W)	0.009	0.069	0.134	0.894	-0.126	0.145					
Model 2: PR → BI (Gender)	Constant	4.466	0.118	37.804	**<0.001*** **	4.234	4.698	0.013	0.000	2.154	0.035 (0,852)	0.093
	Perceived risk (X)	-0.076	0.036	-2.102	**0.036***	-0.147	-0.005					
	Gender (W)	-0.001	0.201	-0.004	0.996	-0.395	0.394					
	Interaction effect (X × W)	0.011	0.062	0.187	0.852	-0.109	0.132					
Model 3: PCV → BI (Gender)	Constant	0.317	0.169	1.873	0.062	-0.016	0.650	**0.603**	**0.005**	**242.225**	**6.578 (0,011*)**	**<0.001*** **
	Perceived customer value (X)	0.936	0.040	23.296	**<0.001*** **	0.857	1.015					
	Gender (W)	0.754	0.292	2.580	**0.010****	0.180	1.328					
	† Interaction effect (X × W)	-0.177	0.069	-2.565	**0.011***	-0.313	-0.041					

Key: Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Behavioural intention (BI); Standard error (SE); Lower level confidence interval (LLCI); Upper-level confidence interval (ULCI); Independent variable (X); Moderating variable (X); Change (Δ)

Note: *$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.001$;

† Interaction effect is further explored in Table 6.28

In **Model 1** (R^2 = 0.233; F = 48.363; $p \leq 0.001$) the aim was to determine whether the direction and strength of the effect of social influence on behavioural intention would depend on a consumer's gender. The results reported in Table 6.27 reveal a positive but non-significant (p = 0.894) moderating impact of gender on the effect of social influence on behavioural intention (b = 0.009; t = 0.134; LLCI – ULCI range included 0: -0.126 to 0.145). It is also noted that, when adding the interaction term (X × W) to the model, there was no change in the coefficient of determination, indicating no significant moderating effect (R^2 change = 0.000; F(0,894) = 0.018).

Model 2 (R^2 = 0.013; F = 2.154; p = 0.093) examined whether the direction and strength of the effect of perceived risk on behavioural intention would depend on a consumer's gender. The results show a positive effect (b = 0.011), but the interaction effect was regarded as insignificant (p = 0.852; t = 0.187; LLCI – ULCI range included 0: -0.109 to 0.132). Consequently, the effect of perceived risk on behavioural intention is not conditional upon a consumer's gender and is therefore not regarded as a moderator. The coefficient of determination confirms that gender has no statistical impact on the relationship between perceived risk and behavioural intention (R^2 change = 0.000; F(0,852) = 0.035).

Model 3 (R^2 = 0.603; F = 242.225; $p \leq 0.001$) explored whether the relationship between perceived customer value and behavioural intention is conditional upon a consumer's gender. The results reported in Table 6.27 show that the effect of positive perceived customer value (b = 0.936) on behavioural intention is negative and significant (b = -0.177; t = -2.565; $p \leq 0.05$; LLCI – ULCI range did not include 0: -0.313 to -0.041) when the interaction term of gender (X × W) is added to the equation. The moderating effect is confirmed by the significant change in the coefficient of determination when the moderating effect of gender is included in the model (R^2 change = 0.005; F(0,011) = 6.578). To further probe where the differences between gender groups lie on the effect between perceived customer value and behavioural intention, Johnson-Neyman intervals and a simple slope analysis were conducted.

Results of the Johnson-Neyman intervals conducted to better understand the nature of the moderating effect of gender on the relationship between perceived customer value and behavioural intention are shown in Table 6.28.

Table 6.28: Conditional effects of the focal predictors at values of the moderator – moderating effect of gender on the relationship between perceived customer value and behavioural intention

Interaction	Gender group	Effect	SE	*t*	*p*	LLCI	ULCI
†PCV → BI	Female	0.936	0.040	23.296	**<0.001*** **	0.857	1.015
	Male	0.759	0.056	13.531	**<0.001*** **	0.649	0.869

Key: Perceived customer value (PCV); Behavioural intention (BI)

Note: ****p* ≤ 0.001

As can be seen from Table 6.28, the interaction effect between perceived customer value and behavioural intention, albeit small, is stronger under the condition of females (0.936; *t* = 23.296; *p* ≤ 0.001; LLCI – ULCI range includes 0: 0.857 to 1.015), compared to males (0.759; *t* = 13.531; *p* ≤ 0.001; LLCI – ULCI range did not include 0: 0.649 to 0.869). The conditional effect of gender on the relationship between perceived customer value and behavioural intention is also graphically presented using a simple slope representation (see Figure 6.14).

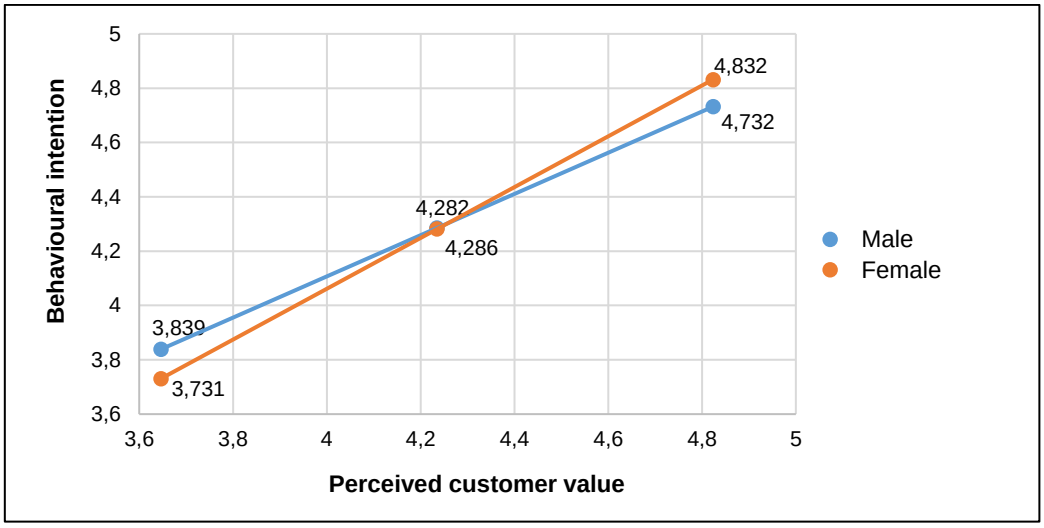

Figure 6.14: Simple slope analysis - Gender as moderator on the effect of perceived customer value on behavioural intention

As can be seen from Figure 6.14, the line is somewhat steeper for female consumers than male consumers, which implies that the behavioural intention to continue using same-day delivery apps increase more for female consumers as their perceived value of using these apps increases. Although the difference is small, it can be inferred that female consumers place slightly more importance on the value derived from using same-day delivery apps than male consumers. The results might be explained by the fact that women are more attracted to exclusivity and uniqueness as attributes of products/services and are therefore prepared to pay higher prices to get these

attributes (Stan, 2015: 1596). Contrary to women, men are more task-oriented and tend to compromise less on lower prices (Stan, 2015: 1596). As a result, the perceived value women derive from using same-day delivery apps compensates for the sacrifice they must make to use the app, and therefore perceived customer value influences female consumers' intention to continue using same-day delivery apps.

The moderating effect of generational cohort on the relationship between the independent variables and behavioural intention will be explored next.

6.6.3.2 The moderating effect of generational cohort on the relationship between the independent variables and behavioural intention

Once again, three models exploring the effects of generational cohort on the interrelationship between social influence (model 4), perceived risk (model 5), as well as perceived customer value (model 6) and behavioural intention were analysed using a three-step process. After estimating the unmoderated equation representing the extent to which Y is predicted by X, the determination of the moderated relationship was assessed by considering the change in R^2. A significant moderating effect exists if the R^2 change is statistically significant ($p \leq 0.05$). Once more, significant moderating effects were further investigated by means of assessing Johnson-Neyman intervals and conducting a simple slope analysis.

The following hypothesised moderation models, regarding the interaction effect of generational cohort, were tested and the results are reported in Table 6.29:

- **Model 4** tested whether the effect of *social influence* on behavioural intention was conditional upon a consumer's generational cohort.
- **Model 5** tested whether the effect of *perceived risk* on behavioural intention was conditional upon a consumer's generational cohort.
- **Model 6** tested whether the effect of *perceived customer value* on behavioural intention was conditional upon a consumer's generational cohort.

The interaction effect of generational cohort on the relationship between the independent variables (social influence, perceived risk and perceived customer value) and behavioural intention is reported in Table 6.29 below. The four original generational cohorts were clustered into two groups due to the small sample sizes observed with the 1950 – 1969 (n = 19) and the 2001 – 2003 (n = 26) cohorts. The following two generational cohorts are therefore explored: Group 1: 1950 – 1989 (n = 196) and Group 2: 1990 – 2003 (n = 289).

Table 6.29: Interaction effect of generational cohort on the relationship between the independent variables (social influence, perceived risk and perceived customer value) and dependent variable (behavioural intention)

								Model summary				
Model		**Unstandardised coefficient (*b*)**	**SE**	***t***	***p***	**LLCI**	**ULCI**	**R^2**	**$R^2\Delta$**	**F**	**FΔ (*p*)**	***p***
Model 4: SI → BI (Gen. cohorts)	Constant	2.973	0.161	18.411	**<0.001*** **	2.656	3.290	0.239	0.004	50.345	2.701 (0,101)	**<0.001*** **
	Social influence (X)	0.324	0.041	7.883	**<0.001*** **	0.243	0.405					
	Generational cohort (W)	-0.321	0.239	-1.345	0.179	-0.791	0.148					
	Interaction effect (X × W)	0.100	0.061	1.644	0.101	-0.020	0.221					
Model 5: PR → BI (Gen. cohorts)	Constant	4.380	0.128	34.103	**<0.001*** **	4.128	4.632	0.015	0.002	2.494	0.909 (0,341)	0.059
	Perceived risk (X)	-0.049	0.038	-1.297	0.195	-0.124	0.025					
	Generational cohort (W)	0.197	0.193	1.021	0.308	-0.182	0.576					
	Interaction effect (X × W)	-0.057	0.060	-0.953	0.341	-0.176	0.061					
Model 6: PCV → BI (Gen. cohorts)	Constant	0.878	0.183	4.799	**<0.001*** **	0.518	1.237	**0.605**	**0.006**	**245.748**	**7.355 (0,007**)**	**<0.001****
	Perceived customer value (X)	0.799	0.043	18.426	**<0.001*** **	0.714	0.884					
	Generational cohort (W)	-0.704	0.276	-2.547	**0.011***	-1.247	-0.161					
	◊ Interaction effect (X × W)	0.178	0.065	2.712	**0.007****	0.049	0.306					

Key: Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Behavioural intention (BI); Standard error (SE); Lower level confidence interval (LLCI); Upper-level confidence interval (ULCI); Independent variable (X); Moderating variable (X); Change (Δ)

Note:**p* ≤ 0.05; ***p* ≤ 0.01; ****p* ≤ 0.001;

◊ Interaction effect is further explored in Table 6.30

Model 4 (R^2 = 0.239; F = 50.345; $p \leq 0.001$) explained the conditional effect of generational cohort (age group) on the relationship between social influence and behavioural intention. From the results reported in Table 6.29 above, a positive (b = 0.100) but statistically insignificant moderating effect is evident when the interaction term (X × W) is added to the model (p = 0.101; t = 1.644; LLCI – ULCI range includes 0: -0.020 to 0.221). It is also noted that when the interaction effect of generational cohort is added to the model measuring the effect of social influence on behavioural intention, the change in the coefficient of determination is not significant (R^2 change = 0.004; F(0,101) = 2.701)

In **Model 5** (R^2 = 0.015; F = 2.494; p = 0.059) the aim was to determine whether the direction and strength of the effect of perceived risk on behavioural intention would depend on a consumer's generational cohort. The results reported in Table 6.29 reveal a negative but statistically insignificant (p = 0.341) moderating impact of generational cohort on the effect of perceived risk on behavioural intention (b = -0.057; t = -0.953; LLCI – ULCI range included 0: -0.176 to 0.061). When adding the interaction term (X × W) to the model, only a small change in the coefficient of determination is noted, indicating generational cohort has no statistically significant moderating effect of perceived risk on behavioural intention (R^2 change = 0.002; F(0,341) = 0.909).

In the last interaction model, **Model 6** (R^2 = 0.605; F = 245.748; $p \leq 0.001$), the direction and magnitude of the relationship between perceived customer value and behavioural intention, conditional upon a consumer's generational cohort, was examined. A positive and statistically significant interaction effect of perceived customer value on behavioural intention, under the condition of generational cohort, is evident (b = 0.178; t = 2.712; $p \leq 0.001$; LLCI – ULCI range did not include 0: 0.049 to 0.306) (see Table 6.29). The moderation effect is confirmed by the significant change in the coefficient of determination when the moderating effect of generational cohort is included in the model (R^2 change = 0.006; F(0,007) = 7.355). To further investigate where the differences between generational cohorts lie in the effect of perceived customer value on behavioural intention, Johnson-Neyman intervals were assessed and a simple slope analysis was conducted.

Results of the Johnson-Neyman intervals conducted to better understand the nature of the moderating effect of generational cohort on the relationship between perceived customer value and behavioural intention are shown in Table 6.30.

Table 6.30: Conditional effects of the focal predictors at values of the moderators – moderating effect of generational cohort on the relationship between perceived customer value and behavioural intention

Interaction	Generational cohort	Effect	SE	*t*	*p*	LLCI	ULCI
◊PCV → BI	1950 – 1989	0.977	0.049	19.908	**<0.001*** **	0.880	1.073
	1990 – 2003	0.799	0.043	18.426	**<0.001*** **	0.714	0.884

Key: Perceived customer value (PCV); Behavioural intention (BI)

Note: *** $p \leq 0.001$

As can be seen from Table 6.30, the interaction effect between perceived customer value and behavioural intention is slightly stronger under the condition of the Baby Boomer and Generation X cohort (1950 – 1989) (0.977; $t = 19.908$; $p \leq 0.001$; LLCI – ULCI range includes 0: 0.880 to 1.073), compared to the Generation Y and Z cohort (1990 – 2003), although the effect is relatively small (0.799; $t = 18.426$; $p \leq 0.001$; LLCI – ULCI range did not include 0: 0.714 to 0.884). The conditional effect of generational cohort on the relationship between perceived customer value and behavioural intention is also graphically presented using a simple slope representation (see Figure 6.15).

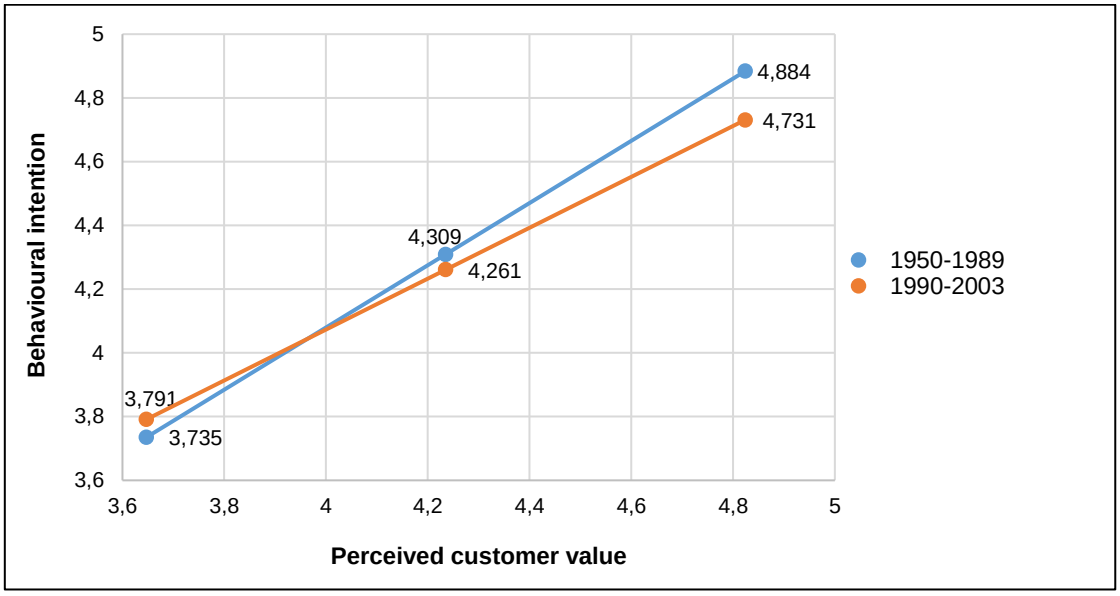

Figure 6.15: Simple slope analysis – Generational cohort as moderator on the effect of perceived customer value on behavioural intention

As can be seen from Figure 6.15, the line is slightly steeper for the Baby Boomer and Generation X cohort (1950 – 1989) than for the Generation Y and Z cohort (1990 – 2003), which implies that behavioural intention to continue using same-day delivery apps increases more for Baby Boomers

and Generation X-ers (which can be regarded as older consumers) as their perceived value of using same-day delivery apps increases. These results suggest that, for the older age group (Baby Boomers and Generation X), the benefits derived from using same-day delivery apps are to some extent more important than for the younger age group (Generation Y and Z), although the effect is small. The results might suggest that the older generation (Baby Boomers and Generation X) has limited funds, due to perhaps being retired or nearing retirement, being more conscious about saving money or having a family with children, and therefore the monetary sacrifice is higher than for the younger generation (Generation Y and Z). Consequently, the benefits Baby Boomers and Generation X-ers receive from using same-day delivery apps must be worth the sacrifices, and perceived value is therefore more significant in their intentions to continue using same-day delivery apps.

The results provide a measure of supportive evidence for H_a4 and empirical research objective 6: to empirically assess the interaction effects between the independent variables and the dependent variable, and two demographic conditions (moderators), namely generational cohort and gender. The results suggest that demographic variables (generational cohort and gender) as moderators only marginally impact the relationship between perceived customer value and behavioural intention. By inference from the moderation analysis and results discussed in the preceding section, the hypothesis related to the moderating effects between the various independent variables and behavioural intention can be partially accepted (H_a4: *Generational cohort and gender significantly moderate the relationship between the independent variables and behavioural intention to continue using same-day delivery apps*).

The last stage in the inferential and multivariate statistical analysis process is testing for significant group mean differences to ascertain the source of differences (if any) from consumers from various demographic groups. The results are reported in the next section.

6.6.4 TEST FOR GROUP MEAN DIFFERENCES BETWEEN INDIVIDUALS FROM DIFFERENT DEMOGRAPHIC BACKGROUNDS REGARDING THEIR BEHAVIOURAL INTENTION

The purpose of this section was to address empirical research objective 7: to assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps. Group mean differences were explored for interest sake and non-comparative purposes.

Independent *t*-tests were conducted to determine if there were statistically significant differences between the mean scores of two categories or independent groups and one continuous variable (Wiid & Diggines, 2021: 323). For this purpose, independent sample *t*-tests were conducted to assess whether consumers varying in demographic variables (categorical variables: generational cohort and gender) differ significantly when comparing the mean scores of the observed continuous variables – social influence, perceived risk, perceived customer value and behavioural intention.

6.6.4.1 Independent sample t-test: Gender

An independent sample *t*-test was conducted to compare social influence, perceived risk, perceived customer value and behavioural intention for female and male consumers. According to Levene's test for equality of variances, equal variances were assumed between both gender groups and social influence (p = 0.260), perceived risk (p = 0.050), perceived customer value (p = 0.131) and behavioural intention (p = 0.131), as the significance values were relatively large ($p \geq 0.05$). The assumption of homogeneity of variances is therefore met in this analysis.

The results of the independent sample *t*-test and mean scores investigating the relationships between gender and the various observed variables are presented in Table 6.31.

Table 6.31: Independent sample t-test – Gender

Construct	Total (n = 485)	Gender	
		Female (n = 337)	**Male** (n = 145)
Social influence	$\bar{x}$ = 3.83 s = 0.816	$\bar{x}$ = 3.82 s = 0.836	$\bar{x}$ = 3.85 s = 0.778
	Test statistics	*Equal variances assumed ($p \geq 0.05$)* *Levene's test: F = 1,271; p = 0.260* *t-test: $t_{(480)}$ = -0.308; Sig. (2-tailed) = 0.759*	
Perceived risk	$\bar{x}$ = 3.12 s = 0.969	$\bar{x}$ = 3.12 s = 0.938	$\bar{x}$ = 3.10 s = 1.045
	Test statistics	*Equal variances assumed ($p \geq 0.05$)* *Levene's test: F = 3,868; p = 0.050* *t-test: $t_{(480)}$ = 0.228; Sig. (2-tailed) = 0.820*	
Perceived customer value	$\bar{x}$ = 4.19 s = 0.550	$\bar{x}$ = 4.18 s = 0.537	$\bar{x}$ = 4.21 s = 0.587
	Test statistics	*Equal variances assumed ($p \geq 0.05$)* *Levene's test: F = 0,577; p = 0.448* *t-test: $t_{(480)}$ = -0.526; Sig. (2-tailed) = 0.599*	

Construct	Total (n = 485)	Gender	
		Female (n = 337)	Male (n = 145)
Behavioural intention	$\bar{x}$ = 4.24 s = 0.624	$\bar{x}$ = 4.23 s = 0.638	$\bar{x}$ = 4.26 s = 0.596
	Test statistics	*Equal variances assumed ($p \geq 0.05$)* *Levene's test: F = 2,283; p = 0.131* *t-test: $t_{(480)}$ = -0.585; Sig. (2-tailed) = 0.559*	

Notes: $\bar{x}$ = mean; s = standard deviation

Results of the independent sample *t*-test, as displayed in Table 6.31, indicate that there were no statistically significant differences between females and males with regard to social influence ($t_{(480)}$ = -0.308; p = 0.759), perceived risk ($t_{(480)}$ = 0.228; p = 0.820), perceived customer value ($t_{(480)}$ = -0.526; p = 0.599) and behavioural intention ($t_{(480)}$ = -0.585; p = 0.559). The extent to which the means between the gender groups differed was trivial across all observed variables. Accordingly, it is inferred that there are no noteworthy unconformities between female and male consumers when comparing their social influence, perceived risk, perceived customer value and behavioural intention ($p \geq 0.05$).

6.6.4.2 Independent sample t-test: Generational cohort

An independent *t*-test was conducted to compare social influence, perceived risk, perceived customer value and behavioural intention for two generational cohorts. As with the moderation analysis, the four original generational cohorts were clustered into two groups due to the small sample sizes observed with the 1950 – 1969 (n = 19) and the 2001 – 2003 (n = 26) cohorts. The following two generational cohorts are therefore explored in this analysis: Group 1: 1950–1989 (n = 196) and Group 2: 1990–2003 (n = 289).

According to Levene's test for equality of variances, as reported in Table 6.32 below, equal variances were assumed between the cohort groups and social influence (p = 0.230), perceived risk (p = 0.948) and perceived customer value (p = 0.055), as the significance values of these constructs exceeded 0.05. The assumption of homogeneity of variances is therefore met for these constructs. Equal variances were not assumed between the cohort groups and behavioural intention (p = 0.032), with a relatively small significance value ($p \leq 0.05$). As a result, unpooled variances and a correction to the degrees of freedom were used in calculating and analysing the results and differences between the two groups.

The results of the independent sample *t*-test and mean scores investigating the relationship between generational cohorts and the various observed variables are displayed in Table 6.32.

Table 6.32: Independent sample t-test – Generational cohorts

Construct	Total (n = 485)	Generational cohort	
		1950–1989 (n = 196)	**1990–2003** (n = 289)
Social influence	$\bar{x}$ = 3.83 *s* = 0.816	$\bar{x}$ = 3.80 *s* = 0.865	$\bar{x}$ = 3.85 *s* = 0.783
	Test statistics	*Equal variances assumed (p ≥ 0.05)* *Levene's test: F = 1,447; p = 0.230* *t-test: $t_{(483)}$ = 0.686; Sig. (2-tailed) = 0.493*	
Perceived risk	$\bar{x}$ = 3.12 *s* = 0.969	$\bar{x}$ = 2.94 *s* = 0.954	$\bar{x}$ = 3.24 *s* = 0.962
	Test statistics	***Equal variances assumed (p ≥ 0.05)*** ***Levene's test: F = 0,004; p = 0.948*** ***t-test: $t_{(483)}$ = 3.373; Sig. (2-tailed) = <0.001***** ***Cohen's d = 0.321 (small practical effect)***	
Perceived customer value	$\bar{x}$ = 4.19 *s* = 0.550	$\bar{x}$ = 4.19 *s* = 0.574	$\bar{x}$ = 4.18 *s* = 0.535
	Test statistics	*Equal variances assumed (p ≥ 0.05)* *Levene's test: F = 3,689; p = 0.055* *t-test: $t_{(483)}$ = -0.092; Sig. (2-tailed) = 0.927*	
Behavioural intention	$\bar{x}$ = 4.24 *s* = 0.624	$\bar{x}$ = 4.26 *s* = 0.671	$\bar{x}$ = 4.22 *s* = 0.591
	Test statistics	*Equal variances not assumed (p ≤ 0.05)* *Levene's test: p = 0.032** *t-test: $t_{(382.515)}$ = -0.731; Sig. (2-tailed) = 0.465*	

Notes: **p* ≤ 0.05; ***p* ≤ 0.001; $\bar{x}$ = mean; *s* = standard deviation

Results of the independent sample *t*-test, as shown in Table 6.32, indicate that there were no statistically significant differences between the Baby Boomer and Generation X cohort (1950 – 1989) and the Generation Y and Generation Z cohort (1990 – 2003) with regard to social influence ($t_{(483)}$ = 0.686; *p* = 0.493), perceived customer value ($t_{(483)}$ = -0.092; *p* = 0.927) and behavioural intention ($t_{(382.515)}$ = -0.731; *p* = 0.465; equal variances not assumed). The magnitude of the differences in the means was also very small across these observed variables. Accordingly, it is inferred that there are no remarkable unconformities between generational cohorts when comparing their social influence, perceived customer value and behavioural intention (*p* ≥ 0.05).

Results of the independent sample *t*-test, reported in Table 6.32, furthermore indicate that there were significant mean differences between the Baby Boomer and Generation X cohort (which can be considered the older cohort) and the Generation Y and Generation Z cohort (which can be considered the younger cohort) concerning perceived risk ($t_{(483)}$ = 3.373; *p* ≤ 0.001). The mean

score for the Generation Y and Z cohort (1990 – 2003) was slightly higher ($\bar{x}$ = 3.24) than for the Baby Boomer and Generation X cohort (1950 – 1989) ($\bar{x}$ = 2.94) ($\bar{x}$ difference = 0.299). The slight difference in the mean scores could be attributed to the older generation (Baby Boomers and Generation X) disagreeing to some extent that perceived risk influenced their behavioural intention to continue using same-day delivery apps ($\bar{x}$ = 2.94), compared to the younger generation (Generation Y and Z) ($\bar{x}$ = 3.24). Baby Boomers and Generation X (the older cohort) seems to be more risk-averse than the Generation Y and Generation Z cohort (the younger cohortn). Cohen's *d* was investigated to establish the effect of the invariance between the generational cohorts and perceived risk. Despite achieving statistical significance, the actual differences in mean scores were quite small (*d* = 0.312) (Cohen classifies 0.2 as a small effect, 0.5 as a moderate effect and 0.8 as a large effect) (Pallant, 2016: 267).

The conclusion was drawn that Generation Y and Z consumers (born between 1990 and 2003) are influenced more by perceived risk when deciding whether to continue using same-day delivery apps than consumers belonging to the Baby Boomer and Generation X cohort (born between 1950 and 1989), albeit to a small degree. It could be inferred that, because Generation Y-ers and Generation Z generally tend to shop online more frequently and broadly than Baby Boomers and Generation X, they have more likely been exposed to online fraud and, as a result, are more sceptical and cautious of adopting new online shopping platforms. On the contrary, it can be inferred that during the COVID-19 pandemic and the need for social distancing, Baby Boomers and Generation X-ers (or the older generation) offset the risk of physically having to go to the store, increasing their chances of contracting COVID-19, with the minimal risk associated with purchasing products through a reputable same-day delivery app.

The test for group mean differences provided supporting evidence for empirical research objective 7: to assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps. No meaningful differences could be found between individuals from different generational cohorts or genders concerning their intentions to continue using same-day delivery apps. Refer to Annexure J for the comprehensive results discussed in the preceding section.

This concludes the descriptive, inferential and multivariate statistical analysis process. Conclusions regarding the hypotheses, based on the results discussed in this chapter, are summarised in the following section.

6.7 CONCLUSIONS REGARDING THE RESEARCH HYPOTHESES

The results of the statistical analyses discussed in this chapter provide supporting evidence for the acceptance and/or rejection of the null hypothesis.

To recap, the statistical analysis process unravelled as follows: the initial theorised conceptual model (see Chapter 4, Figure 4.1) was subjected to CFA where the model fit, reliability and validity of the research instrument and measurement model were assessed (refer to section 6.4.1). The CFA results revealed mediocre model fit indices, unsatisfactory convergent validity and a lack of discriminant validity between the 11 observed independent variables. As a result, 9 of the original 11 hypotheses stated in Chapter 4 as factors that theoretically influence South African consumers' behavioural intention to continue using same-day delivery apps, could not be proven statistically.

Remedial action was then taken to identify the problems in the original measurement model and a revised measurement model was developed that more adequately fit the data (refer to section 6.4.2 and Figure 6.3). Two of the original observed independent constructs prevailed, namely social influence (stated as H_a1) and perceived risk (stated as H_a2), although some scale items were removed to improve the validity of the model. Additionally, a new latent variable (perceived customer value) emerged from the data with 17 scale items' path estimates clustering together. A third hypothesis was therefore stated as research suggests that consumer values are useful predictors of behavioural intention because a consumer's decisions are susceptible to multiple consumption values (H_a3). Consequential to the outcome of the initial CFA assessment and the development of a revised model, a fourth hypothesis (H_a4), measuring the moderating effect of two demographic variables on the relationship between the independent and dependent variables, was stated. Further statistical analysis was therefore conducted using the revised measurement model presented in Figure 6.3 and the three latent constructs – social influence, perceived risk and perceived customer value.

The hypotheses were tested by means of the SEM analysis reported in section 6.6.2.2. Results showed that the relationship between social influence and behavioural intention (H1) was negative but not statistically significant (p = 0.651). Additionally, results showed that perceived risk negatively impacts behavioural intention (H2), but the results were also statistically insignificant (p = 0.585). Accordingly, H_a1 and H_a2 were not supported and the null hypothesis is accepted for both hypotheses. In addition, the results revealed a positive and statistically significant relationship between perceived customer value and behavioural intention (H3) (β = 0.857; $p \leq 0.001$), thereby supporting H_a3 and rejecting the null hypothesis. Lastly, the moderation analysis provided

supporting results to partially accept H_a4 (refer to section 6.6.3). Generational cohort and gender do not significantly moderate the relationship between social influence and perceived risk and behavioural intention to continue using same-day delivery apps in a South African context; however, perceived customer value is proven to be conditional upon a consumer's generational cohort and gender, albeit to a small effect.

A summary of the hypotheses, the outcome and the statistical support for accepting or rejecting the hypotheses is given in Table 6.33.

Table 6.33: Outcomes of the research hypotheses

Construct	Alternative hypothesis	Accepted/ rejected	Statistical support
H_a1: Social influence	There is a significant relationship between social influence and consumers' behavioural intention to continue using same-day delivery apps.	Rejected	• The SEM analysis revealed no statistically significant relationship: β = -0.026; t = 0.452; p = 0.651(refer to section 6.6.2 and Table 6.26)
H_a2: Perceived risk	There is a significant and negative relationship between perceived risk and consumers' behavioural intention to continue using same-day delivery apps.	Rejected	• The SEM analysis revealed no statistically significant relationship: β = -0.020; t = -0.546; p = 0.585 (refer to section 6.6.2 and Table 6.26)
H_a3: Perceived customer value◊	There is a significant relationship between perceived customer value and consumers' behavioural intention to continue using same-day delivery apps.	**Accepted**	• The SEM analysis revealed a statistically significant relationship between perceived customer value and behavioural intention: β = 0.857; t = 11.256; $p \leq 0.001$) (refer to section 6.6.2 and Table 6.26) *Additional results* • CFA revealed acceptable composite reliability (0.930) and acceptable AVE due to high composite reliability (0.439) (refer to section 6.4.2.2 and Table 6.22) • Discriminant validity was observed between perceived customer value and behavioural intention (0.849) (refer to section 6.4.2.2 and Table 6.23) • Acceptable mean (4.19), standard deviation (0.550), skewness (-0.56) and kurtosis (0.22) values (refer to section 6.5 and Table 6.24) • Pearson's r revealed a significant and high positive correlation between perceived customer value and behavioural intention: r = 0.773; $p \leq$ 0.001 (refer to section 6.6.1, Table 6.25 and Figure 6.10)
H_a4: Moderators (generational cohort and gender)†	Generational cohort and gender significantly moderate the relationship between the independent variables and behavioural intention to continue using same-day delivery apps.	**Partially accepted**	• Generational cohort and gender do not significantly moderate the relationship between social influence and perceived risk and behavioural intention • Generational cohort and gender significantly moderate the relationship between perceived customer value and behavioural intention, although the effect is considered small (refer to section 6.6.3)

Notes: † Revised moderating hypothesis due to the disproving of the original measurement model; ◊ A new latent variable emerged from the CFA results (see section 6.4.2)

Source: Author's own compilation

The research hypotheses are interpreted below in accordance with supporting literature in the field. Previous studies in the field of technology acceptance have revealed that the acceptance of a specific technology is influenced by various factors that can vary across different technological and cultural contexts (Miladinovic & Xiang, 2016: 49; Van Niekerk, 2020: 270; Venkatesh et al., 2012: 158). Therefore, it is understandable that not all of the hypotheses formulated in this South African study were supported.

6.7.1 HYPOTHESIS 1: THERE IS A SIGNIFICANT RELATIONSHIP BETWEEN SOCIAL INFLUENCE AND CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

The inferential and multivariate statistics reported above provide supporting evidence for hypothesis 1 to be **rejected**. The data revealed that social influence does not have a statistically significant influence on consumers' behavioural intention to continue using same-day delivery apps (β = -0.026; t = 0.452; p = 0.651) (refer to section 6.6.2 and Table 6.26). Social influences occur when individuals are predisposed by the thoughts, opinions, behaviours, attitudes and feelings that result from interactions with others, which are then considered to be socially acceptable behaviours (Rashotte, n.d.). Individuals generally develop intentions towards technology when encouraged and motivated by the people close to them and whose opinions they value, such as friends, family members and peers.

The results in the research study regarding social influence were found to be different in comparison with other studies that have applied the UTAUT2 as a guiding model, such as Elango et al. (2019: 1), Karulkar et al. (2019: 158), Lee et al. (2019: 9), Muangmee et al. (2021: 1297) and Zhao and Bacao (2020: 10). However, other studies in the relevant area have rejected the impact of social influence. For instance, in understanding the determinants of continuance intention to use a specific on-demand mobile app in Indonesia, Erwanti et al. (2018: 14) could not find social influence to significantly impact behavioural intention. Flores and Castaño (2020: 25) and Rasli et al. (2020: 679) could also not find a substantial relationship between social influence and the behavioural intention to use food delivery apps.

It can be concluded that South African consumers' decisions to continue using same-day delivery apps are not influenced by people who are important to them (scale item SI1) and influence their behaviour (scale item SI3), or whose opinions they value (scale item SI2), such as friends, family members and peers. Researchers who came to the same conclusion state that this may be due to the fact that app reviews and expert opinions are widely available online; thus consumers may

rely more on online reviews and ratings provided by previous users who have tried same-day delivery apps rather than recommendations from essential or influential people (Flores & Castaño, 2020: 37; Miladinovic & Xiang, 2016: 51; Van Niekerk, 2020: 271). Furthermore, the fact that the available same-day delivery apps in the South African market are offered mainly by reputable retailers, restaurants and intermediaries might make consumers comfortable using these same-day delivery apps without referrals from others as they are accustomed to the retailers/restaurants and imply certain qualities and benefits to the brand.

6.7.2 HYPOTHESIS 2: THERE IS A SIGNIFICANT AND NEGATIVE RELATIONSHIP BETWEEN PERCEIVED RISK AND CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

By inference from the results discussed in this chapter, hypothesis 2 is **rejected**. The data revealed that perceived risk had a negative but insignificant influence on consumers' behavioural intention to continue using same-day delivery apps (β = -0.020; t = -0.546; p = 0.585) (refer to section 6.6.2 and Table 6.26).

Perceived risk was theorised as an exogenous mechanism to be included in the conceptual model. Due to perceived risk being considered a major deterrent that impedes consumers from shopping online or via mobile apps, the construct was included and argued to help increase the applicability and predictive power of the conceptual model. An inverse relationship was hypothesised between consumers' perceived risk and behavioural intention, suggesting that individuals with high perceived risk are more likely to avoid mobile apps and might choose offline retailing as their preferred medium to shop (Kaushik et al., 2015: 22).

The outcomes of the research study are inconsistent with results reported in prior research, for example Ali and Maideen (2019: 375), Arora and Malik (2020: 106), Gupta et al. (2018: 57), Hussein and Saad (2016: 46), Kaushik et al. (2020: 22), Marriott and McLean (2019: 4) and Verkijika (2018: 1673). However, the same insignificant effect of perceived risk on behavioural intention was reported by Monilakshmane and Rajeswari (2018: 153), who explored the impact of perceived risks on users' intention to use financial service mobile apps. Similarly, in a South African study expanding the UTAUT2 Model in exploring the factors that influence the adoption of m-commerce apps for purchasing athletic fashion apparel, perceived risk was found to be insignificant (Van Niekerk, 2020: 274). Chin et al. (2018: 54) as well as Marriott and Williams (2018: 139) report the same insignificant result as found in this South African study.

The insignificant influence of perceived risk on consumers' behavioural intention to continue using same-day delivery apps in a South African context could be a result of the COVID-19 pandemic and civil unrest which occurred at the time of data collection. The COVID-19 pandemic gave rise to the need for home deliveries as individuals sought ways to avoid crowded places and maintain social distancing. Moreover, the civil unrest which occurred in KwaZulu-Natal and Gauteng during July 2021 because of the imprisonment of former President Jacob Zuma for contempt of court resulted in rebellion, violent protest action and looting (The Economist, 2021; The Presidency, 2021). It is therefore plausible that consumers were more concerned about their physical safety and personal health than the risks and uncertainties involved in purchasing products through reputable same-day delivery apps.

6.7.3 HYPOTHESIS 3: THERE IS A SIGNIFICANT RELATIONSHIP BETWEEN PERCEIVED CUSTOMER VALUE AND CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

Based on the discussion provided in this chapter, hypothesis 3 is **accepted**. The construct, perceived customer value, was contextualised as the overall assessment by consumers of product or service utility based on varied benefits and sacrifices (Zeithaml, 1988 in Chahal & Kumari, 2012: 168). More specifically, perceived customer value was regarded as a trade-off between perceived benefits and perceived losses (Hsu & Lin, 2015: 48). It is proposed that the perceived benefits can be viewed in terms of the functional value (performance, ease of use and specific outcomes), economic value (monetary and value for money), emotional value (affective, enjoyment, pleasure and passion) and epistemic value (novelty, open-mindedness and curiosity) derived from using same-day delivery apps.

The results discussed in this chapter revealed that perceived customer value has the strongest influence on consumers' behavioural intention to continue using same-day delivery apps (β = 0.857; t = 11.256; $p \leq 0.001$) (refer to section 6.6.2 and Table 6.26). This finding is consistent with research conducted by Kim, Kim and Wachter (2013: 367), Khan and Kadir (2011: 4094), Mahendar (2017: 100), as well as Zhang et al. (2021: 29), among others. Perceived customer value is argued to strongly correlate with price, quality, sacrifice and satisfaction and is therefore a useful predictor of behaviour (Chang & Dibb, 2012: 256; Jansri, 2018: 1). As the scale items in the perceived customer value construct resembled the notion that same-day delivery apps increase respondents' consumption values, such as enjoyment, quality, value for money and their trade-offs, the construct was deemed fitting. It can be assumed that the perceived benefits and satisfaction received from using same-day delivery apps outweigh the sacrifices made to be able

to use these types of apps. The importance of perceived customer value could also be attributed to consumers placing more emphasis on the benefits offered by same-day delivery apps, compared to the detriments involved in using these apps, because of the COVID-19 pandemic and the civil unrest which was eminent in South Africa at the time of data collection. It is possible that consumers would rather pay the service and delivery fee involved in using same-day delivery apps than risk contracting the virus or entering areas where violent protests took place. As perceived customer value was considered the strongest predictor of behavioural intention, further investigation is warranted.

6.7.4 HYPOTHESIS 4: GENERATIONAL COHORT AND GENDER SIGNIFICANTLY MODERATE THE RELATIONSHIP BETWEEN THE INDEPENDENT VARIABLES AND CONSUMERS' BEHAVIOURAL INTENTION TO CONTINUE USING SAME-DAY DELIVERY APPS

Based on the discussion preceding this section, hypothesis 4 is **partially accepted**. Regression-based moderation analysis was conducted to examine the interaction effects between the independent variables and dependent variable, and consumers' disposition in terms of their gender and generational cohort (refer to section 6.6.3, Tables 6.27 and 6.29). The results reveal only a small interaction effect between perceived customer value and behavioural intention when comparing the two groups.

Johnson-Neyman intervals and a simple slope analysis were performed to better understand the small practical effect detected in the nature of the moderating effect of gender and generational cohort on the relationship between perceived customer value and behavioural intention. The interaction effect was slightly stronger under the condition of females compared to males (refer to section 6.6.3.1 and Table 6.28). The results might be explained by the fact that women are more attracted to exclusivity and uniqueness as attributes of products/services and are therefore prepared to pay higher prices to get these attributes (Stan, 2015: 1596). In contrast, men are more task-oriented and tend to compromise less on lower prices (Stan, 2015: 1596). As a result, the perceived value women derive from using same-day delivery apps compensates for the sacrifice they must make to use the app, and perceived customer value therefore influences female consumers' intention to continue using same-day delivery apps.

Furthermore, the interaction effect between perceived customer value and behavioural intention was slightly stronger under the condition of the Baby Boomer and Generation X cohort (1950 – 1989) compared to the Generation Y and Generation Z cohort (1990 – 2003) (refer to section

6.6.3.2 and Table 6.30). The results might suggest that Baby Boomers and Generation X (or the older cohort) has limited funds, due to perhaps being retired or nearing retirement, being more conscious about saving money or having a family with children, and the monetary sacrifice is therefore higher than for the Generation Y and Generation Z cohort (or the younger cohort). Consequently, the benefits Baby Boomers and Generation X-ers receive from using same-day delivery apps must be worth the sacrifices, and therefore perceived value is more significant in their intentions to continue using same-day delivery apps.

The results contradict the findings of many researchers who found that age and gender significantly moderate the relationship between various independent variables and behavioural intention (refer to Chapter 4, section 4.2.13). Nevertheless, the outcomes of the moderation analysis are supported by other researchers who also found no significant differences between gender and age groups in the acceptance of new technology, such as Baptista and Oliveira (2015: 15), Birch (2009: 88), Faqih and Jaradat (2015: 37), Goulão (2014: 18), Lian and Yen (2014: 140), Pobee and Opoku (2018: 86), Serenko, Turel and Yol (2006: 30) as well as Tan, Ooi, Chong and Hew (2014: 303), to name but a few.

The results are somewhat surprising but could be explained by existing evidence concluding that users from various demographic backgrounds, specifically gender and age groups, utilise mobile phones to a similar extent (Serenko et al., 2006: 30). Due to respondents already being frequent users of mobile shopping platforms in general, and same-day delivery apps specifically, both demographic groups were comfortable using these types of apps. Many respondents also indicated that they mainly used same-day delivery apps offered by restaurants and fast-food outlets, as opposed to grocery-related same-day delivery apps. Consequently, it is plausible that, when purchasing via restaurant/fast-food same-day delivery apps, the main purpose is to acquire food, and the augmented services offered by these types of apps are not of substantial importance to the different demographic groups. Significant differences might have been observed if grocery-related same-day delivery apps were used the most. Due to age and gender discrepancies within the sample, having a larger percentage of female (n = 337; 69.5%) and younger (1990 – 2003) (n = 289; 59.6%) respondents participating in the study, the results may not be fully conclusive and therefore further investigation is required to confirm the moderating role in the model.

Although the empirical analyses resulted in only one hypothesis being accepted, many referenced studies reported in the literature review section reject hypotheses to some extent. The variations in research results across different studies are often attributed to the contextual factors in which the studies are conducted. Scholars like Miladinovic and Xiang (2016: 49) as well as Verkijika

(2018: 1672) agree that cultural and technological contexts play a significant role in shaping the acceptance and usage of technology. When the context changes, it can lead to alterations in theoretical frameworks, including changes in the direction and significance of relationships between variables, as well as the emergence of new relationships (Van Niekerk, 2020: 297). Differences in research results should therefore be regarded as positive, as empirical research critically reflects on specific theories in new contexts, markets or cultural settings, which enhances researchers' abilities to challenge those theories, explore latent weaknesses and encourage the rethinking of those theories. This ultimately leads to the creation of knowledge (Van Niekerk, 2020: 297).

6.8 CONCLUSION

In Chapter 6 the results to investigate the nature of the empirical relationships between the theorised independent variables and consumers' behavioural intention to continue using same-day delivery apps were presented and discussed. An in-depth account was provided of the descriptive as well as the inferential and multivariate statistics of relevance to the research study, which included means and standard deviations, assessing the assumption of normality, CFA, construct descriptives, correlation analysis, SEM, moderation analysis and testing for group mean differences. The results were interpreted to enable the researcher to integrate the discoveries of the literature review with the empirical research findings. The results provided supportive evidence for the formulated research objectives and hypotheses.

The empirical research objectives were achieved in Chapter 6.

Empirical research objective 8: to formulate conclusions and make recommendations for the marketing and retailing industry, and for possible future research, based on the results of the research study, is addressed in the last chapter, Chapter 7. Chapter 7 serves as the concluding chapter of the research study, summarising the key findings, implications, and recommendations for the industry based on the data analysis. It provides a comprehensive overview of the research study's outcomes and presents detailed strategies derived from the results. Additionally, the chapter acknowledges the limitations of the study and offers suggestions for future research directions.

CHAPTER 7:
CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

7.1 INTRODUCTION

Chapter 7 concludes the research study by addressing empirical research objective 8, namely to formulate conclusions and make recommendations for the marketing and retailing industry, and for possible future research, based on the results of the research study. The core conclusions of the study are outlined according to each of the secondary literature and empirical research objectives given in Chapter 1, section 1.4. Thereafter, the research limitations are addressed, and recommendations for industry and latent opportunities for future research projects are highlighted. The chapter and study are concluded with an evaluation of the research study by highlighting the contribution the research makes to academia and the marketing and retail industry, with actionable strategies for retailers. Chapter 7 will first commence with an overview of the research study and a synopsis of each of the preceding chapters in the study.

7.2 BRIEF OVERVIEW OF THE RESEARCH STUDY

The aim of the research study was to close the knowledge gap by providing new insight into consumers' behavioural intention to continue using same-day delivery apps within a South African context, by extending the Unified Theory of Acceptance and Use of Technology (UTAUT2) Model, developed by Venkatesh et al. (2012). The research problem, as discussed in Chapter 1 (section 1.4) and Chapter 5 (section 5.2.1), guided the development of a research question and a primary research objective that served to provide direction to the research process. The research question, from which the specific research objectives were derived, was as follows:

Research question: What factors influence South African consumers' behavioural intention to continue using same-day delivery apps?

From the above research question, the primary research objective was formulated, and secondary research objectives were set in terms of the literature review and empirical study.

The **primary research objective** was to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model.

Chapter 1 introduced the research study and commenced with background information and literature about the mobile app industry, mobile shopping apps and the rise of the on-demand economy, which lay the foundation and rationale for the study. In the first chapter, the research problem and purpose, research question as well as the primary and secondary research objectives of the study were formulated (as reiterated above). The significance of the research study in terms of its potential contribution to knowledge at literature level and practical level was pointed out. After examining the literature, it became evident that a conceptual model exploring consumers' behavioural intention to continue using same-day delivery apps in a South African context was lacking. The proposed research methodology was summarised with the aim of closing the identified gap in the literature, as stated in the purpose of the study. The chapter concluded with a brief overview of the delimitations of the study, the ethical considerations as well as an overview of the chapters to follow.

Chapter 2 outlined the metatheoretical context that formed the definitive boundary of the research study. The discussion included the evolution of the South African retailing industry and the advancements of e-commerce, m-commerce and the mobile app market, with specific focus on the development of the on-demand economy and the relevance of same-day delivery apps in the South African market. The merit and performance of same-day delivery apps globally and locally were debated to provide context to the research study. It was apparent from the discussion provided in Chapter 2 that, during the past few years, there has been a substantial revolution in customer trends and behaviour due to the advancements in mobile technology and the rise of the on-demand economy. Understanding consumers' behaviour towards new technologies enables marketers to adapt their business model accordingly to reach a wider audience.

Chapter 3 continued with a thorough assessment of the development of Venkatesh et al.'s Unified Theory of Acceptance and Use of Technology Models (the UTAUT and UTAUT2) (2003; 2012), which formed the foundation of the conceptual model developed for the purpose of the study. The various constructs of the UTAUT and UTAUT2 Models and the moderators were discussed, and a theoretical analysis was offered of the credibility, validity and limitations of these models. The purpose of Chapter 3 was to assess the scientific and methodological rigour of the UTAUT2 Model and establish its significance in determining consumers' behavioural intention in the milieu of the research study. After an extensive review of the literature pertaining to the UTAUT2 Model and exploring the limitations of the model, it was reasoned that the UTAUT2 Model provided a solid base for explaining consumers' behavioural intention to accept or reject new technology and was therefore used as the foundation to build the conceptual model proposed in the research study.

Chapter 4 followed with the theoretical validation of the proposed conceptual model, measuring consumers' behavioural intention to continue using same-day delivery apps. The constructs identified from several scholarly works and empirically validated results were covered, which have proven to be key determinants in establishing consumers' behavioural intention in various contexts. A theoretically grounded conceptual model for consumers' behavioural intention to continue using same-day delivery apps in a South African context was developed from the comprehensive literature discussion. Theoretical and empirical evidence supported the inclusion of 11 constructs in assessing South African consumers' behavioural intention to continue using same-day delivery apps: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, price value, lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. Theoretical differences were furthermore investigated in the literature which led to the inclusion of two moderators in the development of the conceptual model, namely generational cohort (age) and gender. The proposed conceptual model derived from the metatheoretical integration discussed in Chapter 4 was presented in Figure 4.1.

Chapter 5 detailed the research methodology employed in the research study. The research paradigm and research approach were introduced, followed by a comprehensive discussion and justification of the research design, sampling frame and sampling methods employed to achieve the primary research objective of the research study. An explanation of how the research instrument was developed, administered and validated was provided, followed by a description of the data analysis methods that were applied, as well as the procedures that were followed to adhere to ethical obligations. To summarise, a deductive, quantitative research approach was adopted within the ambit of the post-positivistic research paradigm. Furthermore, to achieve the research objectives of the research study, a cross-sectional survey design was applied. Data were conveniently (non-probability) collected through an online, web-based self-administered questionnaire from a sample of 485 South African consumers who were between the ages of 18 and 65 years, resided in either Gauteng, KwaZulu-Natal or the Western Cape province and who, at the time the study was conducted, used same-day delivery apps. The research instrument was administered by an online data collection company, Springvale Online, which distributed the URL link to the online survey in an e-mail invitation to its database of consumers (members). The research instrument was subjected to an expert panel of reviewers, cognitive interviewing and a pilot study to assess the validity of the content and understandability of the research instrument in general before final data collection began (refer to section 5.2.5.4 for the results of the pre-test).

The empirical results of the study were presented and discussed in Chapter 6. Chapter 6 began with an overview of the profile of respondents who formed part of the research study. Thereafter,

descriptive statistics as well as inferential and multivariate statistical analyses were applied and reported to achieve each of the secondary empirical research objectives. A discussion regarding the outcomes of the research hypotheses and the interpretation of the results in conjunction with existing research concluded Chapter 6. The final step of the empirical research study, which entails discussing and interpreting the findings and stating the conclusions, limitations and recommendations of the study, is dealt with in this final chapter (Chapter 7).

In the sections to follow the results for each of the secondary literature and empirical research objectives that fulfil the primary objective are commented on, and the main conclusions that were drawn from the results are highlighted.

7.3 CONCLUSIONS OF THE RESEARCH STUDY

The primary purpose of the research study was to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model. In pursuit of the primary research objective, several secondary research objectives were formulated, as outlined in Chapter 1 (section 1.4) and recapped above. Conclusions were drawn about each of the specific literature and empirical research objectives, which are discussed in the sections to follow.

7.3.1 CONCLUSIONS REGARDING THE LITERATURE REVIEW

Specific literature research objectives 1 to 6 entailed a comprehensive contextualisation of the metatheoretical framework of the research study, namely consumers' behavioural intention to continue using same-day delivery apps in a South African context, and a theoretical exploration of the relationship dynamics between several relational constructs that were deemed significant in the context of the study. The relationship dynamics between 11 independent constructs and consumers' behavioural intention to continue using same-day delivery apps, as moderated by generational cohort and gender, were examined. The literature research objectives were addressed in Chapters 2 to 4, with a synthesis of the main literature findings presented with a conceptual model in Chapter 4 (Figure 4.1). Chapter 4 therefore served as a theoretical integration and reflective evaluation of the literature review which culminated in a theorised model integrating the factors that influence consumers' behavioural intention to continue using same-day delivery apps.

Conclusions based on each of the specific literature research objectives are discussed next.

7.3.1.1 Literature research objective 1

The first literature research objective was as follows:

Research objective 1:	To discuss mobile apps and same-day delivery app usage from an international and South African context and in relation to the retailing industry.

The specific literature research objective was achieved in Chapter 2, which provided a comprehensive exploration of the evolution of the retail industry in South Africa and the emergence of e-commerce and m-commerce, with specific reference to the on-demand economy and same-day delivery apps. The literature suggests that there is an endless evolution in consumer trends, needs and behaviour due to the constant developments in mobile technology and the rise of the on-demand economy. The emergence of the on-demand economy, together with individuals' precipitated lifestyles, excessive use of technologies and constant access to high-speed Internet, have led to a greater demand for a myriad of mobile shopping apps offering convenience and instant service delivery (Belanche et al., 2020: 2; Elango et al., 2019: 2).

From a South African perspective, the literature indicates that various mobile shopping platforms are being used by South African consumers, who are becoming more technologically astute and expect preferred retailers to offer various channels through which they can purchase (Van Niekerk, 2020: 76), including on-demand services. The worldwide COVID-19 pandemic furthermore gave rise to the need for home deliveries as individuals sought ways to avoid crowded places and maintain social distancing. Additionally, the civil unrest which occurred in KwaZulu-Natal and Gauteng during July 2021 because of the imprisonment of former President Jacob Zuma for contempt of court (The Presidency, 2021) resulted in rebellion, violent protest action and looting (The Economist, 2021). These socio-economic challenges, among others, faced by South African consumers have possibly amplified consumers' need for safer shopping options. Especially for the grocery market, COVID-19 and the civil unrest acted as the trigger that caused the rapid acceleration in the popularity of same-day delivery services in South Africa. The COVID-19 pandemic and nationwide lockdown restrictions, which confined customers to their homes, led to a shift in consumer behaviour patterns and forced the acceleration of online and mobile shopping (Business Tech, 2021a).

The South African same-day delivery app market developed at an astonishing rate; hence the need to investigate the use of same-day delivery apps in more depth, as theory providing

supporting evidence of the factors that influence South African consumers' intention to continue using same-day delivery apps is limited.

7.3.1.2 Literature research objective 2

The second literature research objective was as follows:

Research objective 2:	To assess the scientific and methodological rigour of the UTAUT2 Model to position an improved theoretical paradigm to use the model as the foundational framework for the research study.

Specific literature research objective 2 was achieved in Chapter 3, which focused on the assessment and methodological rigour of the UTAUT and UTAUT2 Models. This evaluation aimed to validate the suitability of the UTAUT2 Model as the foundation for the research study's conceptual model.

The literature review examined the model's purpose, development and application in various contexts. By analysing scholarly works, the following key conclusions were established:

- The UTAUT2 Model's efficacy in the consumer context, its suitability, validity and reliability in explaining diverse technology adoption scenarios, is extensively supported in the literature (e.g. Bühler & Bick, 2013; Gruzd et al., 2012; Hew et al., 2015; Tak & Panwar, 2017; Tan et al., 2017).
- The UTAUT2 Model is recognised as a complex yet compelling model, unbounded in explanatory and predictive power, with reliable empirical and practical relevance (Trojanowski & Kutak, 2017: 95).
- The UTAUT2 Model has better explanatory power than other acceptance models (Gharaibeh & Arshad, 2018: 125) and is proven to be more robust in assessing and predicting behavioural intention and actual use behaviour in a consumer context (Dwivedi et al., 2017: 719; Moghavvemi et al., 2013: 247; Taiwo & Downe, 2013: 48).
- The UTAUT2 Model's key merits and limitations were assessed according to Weber's framework and criteria for evaluating a theory (2012). While demonstrating various strengths, the review also acknowledged limitations. The UTAUT2 Model excels in defining constructs, associations and importance, but shows relative weaknesses in states, events

and parsimony due to complex interactions and the absence of boundary conditions (Tamilmani et al., 2021: 17; Venkatesh et al., 2016: 338) (refer to Chapter 3, section 3.3.3).

- Behavioural intention does not fully consider all possible external factors that can affect the performance of a behaviour. Thus, the role of external variables, such as social and monetary influences, that could potentially hinder or simplify the performance of a behaviour is not fully captured by behavioural intent (Moghavvemi et al., 2013: 247).
- Behavioural intention has a weak predictive and explanatory ability to deal with ambiguity and unexpected events that may occur between the time the intention was formed and the given behaviour was performed. Various internal and external stimuli can alter the temporary intention, rendering behavioural intention inaccurate, unstable and less predictive of actual use behaviour (Moghavvemi et al., 2013: 247). Sheeran and Webb (2016: 506) identified the gap between behavioural intention and actual behaviour as the 'intention-behaviour gap'. For the purpose of the research study, however, use behaviour was not investigated because the causal link between behavioural intention and use behaviour has already been confirmed by several scholars (e.g. Hossain et al., 2017: 15; Lewis et al., 2013: 30; Uphaus et al., 2019: 14; Venkatesh et al., 2003: 468; Yun et al., 2013: 222). It has been argued that the best predictor of actual use is the behaviour an individual intends to perform (Kendrick, 2011), and therefore it was presumed that a consumer's intention to continue using a technology culminates in actual use.
- Behavioural intention is weak in its ability to predict behaviours that are not completely within an individual's volitional control (Moghavvemi et al., 2013: 245). In the context of the research study, the use of same-day delivery apps by consumers is completely volitional as consumers are not obligated to use these types of apps and are free to choose which shopping apps they will adopt.
- The UTAUT2 Model excludes self-efficacy and attitude as direct determinants of behavioural intention (Ahmad, 2014: 3; Moghavvemi et al., 2013: 245). Inexperienced users may view new technological systems or devices as complex, and the confidence an individual has in their ability to use these new technologies has a significant influence on their acceptance of the technologies (Lee & Hsieh, 2009: 1; Wang & Wang, 2008: 405; Yul, 2014: 12-13). Furthermore, various theories (e.g. TPB, TRA and TAM) considered attitude as a direct determinant of behavioural intention, which was omitted from the UTAUT2 Model due to the construct being significant only when specific cognitions (performance expectancy and effort expectancy) were absent from the model. As a result, perceived self-efficacy and attitude towards using technology were incorporated into the conceptual model, drawing upon insight

from models like the TPB and TRA. This addition aims to provide a more thorough understanding of consumers' choices in the context of same-day delivery apps.

From the conclusions presented above, it was deduced that the UTAUT2 Model remains a robust and well-supported model offering a strong foundation to assess and predict technology acceptance behaviours with immense potential for understanding technology adoption across diverse contexts (Samaradiwakara & Gunawardena, 2014: 32; Taiwo & Downe, 2013: 48). Despite its limitations, which were carefully addressed, the UTAUT2 Model provides a strong foundation for exploring consumers' behavioural intention to continue using same-day delivery apps.

7.3.1.3 Literature research objective 3

The third literature research objective for the study was as follows:

Research objective 3:	To identify, in the literature, theoretically and empirically validated constructs that significantly influence consumers' behavioural intention towards new technology.

This specific literature research objective was achieved in Chapter 4. Chapter 4 provided the theoretical validation required for the development of the proposed conceptual model measuring consumers' behavioural intention to continue using same-day delivery apps. Eleven independently developed concepts that have been both theoretically and practically proven were identified as a result of the literature review's extensive exploration of the body of research.

The literature provided theoretical justification affirming the inclusion of the original seven constructs from the UTAUT2 Model used as the foundational framework: performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit and price value. Beyond the established UTAUT2 Model constructs, four additional exogenous mechanisms were identified: lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. These inclusions extend the reach of the UTAUT2 Model and contributed significantly to the wider field of acceptance behaviour research.

Perceived self-efficacy and attitude towards use were specifically included in the conceptual model to address the limitations presented in the literature and debated in specific literature research objective 2 (refer to section 7.3.1.2 above). Recognising the shortcomings of the UTAUT2 Model,

the research study incorporated additional constructs to provide a more comprehensive understanding of consumer decision-making within the context of same-day delivery apps.

7.3.1.4 Literature research objective 4

The fourth literature research objective of the study was as follows:

Research objective 4:	To conceptualise the identified constructs and investigate the theoretical interrelationships between the independent constructs and behavioural intention, relevant to the context of the research study.

Manifested in several related academic works, there are theoretical interrelationships between the 11 identified independent constructs and consumers' behavioural intention and these were empirically supported by previous research. Based on these theoretical discoveries, adequate validation was available to propose that the 11 identified independent constructs exert the same significant influence on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

Conclusions drawn from each of the identified independent constructs, and in line with specific literature research objective 4, are highlighted below.

7.3.1.4.1 Conclusions about the performance expectancy construct

Emerging as a key influencing factor in the UTAUT2 Model, performance expectancy was defined as the degree to which the use of a certain technology, such as same-day delivery apps, is of benefit to a consumer (Venkatesh et al., 2012: 159). In the context of the research study, performance expectancy referred to a consumer having the ability to shop via their mobile device at any time of the day, at any location and thereby saving time and effort, obtaining a fast response through immediate access to products and services and allowing consumers to achieve personal objectives resourcefully and successfully (Van Niekerk, 2020: 137). It was concluded that individuals are more inclined to use a technology that they deem to be useful or that offers them valuable benefits (Gupta et al., 2018: 140).

The literature suggests that performance expectancy is one of the most widely studied constructs in technology adoption research and has proven to be a significant predictor of technology acceptance behaviour (e.g. Chao, 2019: 1; Chopdar & Sivakumar, 2019: 46; Palau-Saumell et al.,

2019: 1; Sair & Danish, 2018: 501; Venkatesh et al., 2012: 160; Zhao & Bacao, 2020: 4). Performance expectancy was investigated in the context of adopting m-commerce, mobile apps and mobile shopping apps in general, and theoretical interrelationships were reported widely in the literature (e.g. Baptista & Oliveira, 2015: 418; Chopdar & Sivakumar, 2019: 53; Fadzil, 2017: 1; Sair & Danish, 2018: 501). The literature furthermore pinpoints performance expectancy as a vital construct in the adoption of related mobile technologies, such as the adoption of online food delivery apps and on-demand mobile services (Erwanti et al., 2018: 13; Flores & Castaño, 2020: 25; Karulkar et al., 2019: 146; Lee et al., 2019: 1; Mensah, 2019: 23; Muangmee et al., 2021: 1297; Rasli et al., 2020: 679; Yapp et al., 2018: 105).

Based on the substantial body of literature validating the interrelationship between performance expectancy and behavioural intention, it was concluded and proposed that performance expectancy will have the same significant influence on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

7.3.1.4.2 Conclusions about the effort expectancy construct

Effort expectancy was contextualised, in relation to the research study, as a measure of ease that is associated with using a mobile app and thus referred to the extent to which users believe that their continued use of same-day delivery apps will be convenient, coherent, logical and free of any effort. Effort expectancy signified how easily a consumer can use same-day delivery apps to shop for goods, make purchase decisions and conveniently receive same-day delivery of ordered products.

A theoretical interrelationship was widely reported in the literature and supported by previous empirical evidence. Research suggests that there is a significant relationship between effort expectancy and individuals' behavioural intention to adopt mobile shopping and mobile apps (e.g. Alalwan et al., 2017: 99; Hew et al., 2015: 1269; Karulkar et al., 2019: 156; Rasli et al., 2020: 685; Venkatesh et al., 2011: 544). The literature related to the online food delivery, or on-demand delivery industry was scarce, but Karulkar et al. (2019: 146), Mensah (2019: 23), Muangmee et al. (2021: 1306) and Rasli et al. (2020: 679) theorised and confirmed a significant influence between effort expectancy and consumers' intention to use on-demand or online food delivery services or apps.

Owing to the wide inclusion of effort expectancy in adoption behaviour research pertaining to m-commerce and mobile shopping apps, it was concluded and proposed that effort expectancy

will have the same significant influence on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

7.3.1.4.3 Conclusions about the facilitating conditions construct

Facilitating conditions signify a user's perception and belief that the necessary infrastructure, resources and support are available to perform a given behaviour (Venkatesh et al., 2012: 159). In relation to the research study, facilitating conditions represented an Internet-enabled smart device, having the capability of downloading and running mobile apps, offering location or device finding capabilities, a stable Internet connection or access to mobile data and a knowledgeable user.

It was concluded from the literature review that there is a theoretical interrelationship between facilitating conditions and behavioural intention. Several researchers have reported a noteworthy influence on consumers' behavioural intention to continue using mobile shopping apps (Chopdar et al., 2018: 120; Miladinovic & Xiang, 2016: 50; Soni et al., 2019: 369; Verkijika, 2018: 1672), food delivery service apps (Karulkar et al., 2019: 159; Musakwa, 2021: iii) and on-demand services (Erwanti et al., 2018: 9; Yapp et al., 2018: 105).

Although opposing results are reported in the literature, Chopdar et al. (2018: 113) argue that users of mobile shopping apps require various skills and resources at their disposal, such as a stable Internet connection, the capabilities of downloading and installing different apps and the skills to use these apps. Appropriate facilitating conditions are essential for the acceptance of technology and may vary meaningfully across technology providers in the consumer market (Palau-Saumell et al., 2019: 6; Vinnik, 2017: 34). As a result, a complementary set of facilitating conditions will increase the likelihood of consumers accepting and using mobile shopping apps, and therefore warranted further investigation in the context of same-day delivery apps in South Africa. It was argued that if the required facilities, resources and support are available, consumers would have heightened intentions to continue using same-day delivery apps. It was resolved and proposed that facilitating conditions will have a significant influence on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

7.3.1.4.4 Conclusions about the social influence construct

Social influence arises when individuals are susceptible to the opinions, thoughts, attitudes, behaviours and emotions of others, which are then considered to be acceptable social behaviours,

whether deliberately or unintentionally (Rashotte, n.d.). The intention to use new technology is generally formed when encouraged by significant others whose opinions matter to the individual. Individuals can be influenced either by mass media or by their interpersonal influencers (Chopdar et al., 2018: 113; Hew et al., 2015: 1273).

Existing literature supports the notion that social influence significantly impacts individuals' behavioural intention to use m-commerce and mobile shopping apps (e.g. Chopdar & Sivakumar, 2019: 42; Lian & Yen 2014: 133; Miladinovic & Xiang, 2016: 22; Tak & Panwar, 2017: 12; Verkijika, 2018: 1672). Current literature, albeit limited, confirms that social influence impacts the behavioural intention to adopt on-demand service delivery apps (Elango et al., 2019: 1) and food delivery services and/or apps (Karulkar et al., 2019: 158; Lee et al., 2019: 9; Muangmee et al., 2021: 1307; Yapp et al., 2018: 105; Zhao & Bacao, 2020: 10).

Social influence was expected to have an impact on consumers' behavioural intentions to use new technology, particularly in emerging economies such as South Africa, where lower-than-average Internet and related technology penetration means that societies will gradually increase their level of trust in new mobile apps as others around them do (Van Niekerk, 2020: 140). As a result, it was concluded and proposed that social influence will have a significant impact on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

7.3.1.4.5 Conclusions about the hedonic motivation construct

Hedonic motivation refers to the pleasure individuals derive from using technology and represents gratification based on emotional responses, sensory pleasure and dreams, which motivate individuals to shop (Venkatesh et al., 2012: 161). In this study hedonic motivations signified consumers' need for pleasure, enjoyment, or entertainment that can be obtained from their engagement with a particular mobile shopping app (Mavuya, 2016: 17).

A vast body of literature theorises a noteworthy interrelationship between hedonic motivations and the intention to continue using a new technological platform, system or device. Prior research, in the context of mobile shopping apps, affirms that hedonic motivation significantly influences the behavioural intention of individuals to adopt m-commerce platforms, mobile shopping and mobile apps (e.g. Chopdar et al., 2018: 122; Hew et al., 2015: 1269; Miladinovic & Xiang, 2016: 50; Verkijika, 2018: 1668), and specifically online food delivery service platforms (Flores & Castaño, 2020: 37; Musakwa, 2021: 60; Rasli et al., 2020: 685; Yeo et al., 2017: 157).

The number of individuals that are turning to food delivery in recent years has increased due to the current pace of life and the opportunity to discover more restaurants and/or retailers that offer delivery services (Rasli et al., 2020: 683). It is also believed that the more users find mobile apps enjoyable, the more likely they are to use them (Miladinovic & Xiang, 2016: 50; Rasli et al., 2020: 683). Using m-commerce apps may give the impression of living a modern lifestyle, eliciting feelings of joy (Van Niekerk, 2020: 143).

From the literature discussion, it was concluded that mobile shopping apps, such as same-day delivery apps, are enjoyable, entertaining and fun to use and will consequently have a significant influence on consumers' behavioural intention to continue using same-day delivery apps in the South African context.

7.3.1.4.6 Conclusions about the habit construct

Habit is described as the involuntary and unconscious behaviour that is goal-directed and is recognised with automaticity (Kim et al., 2005: 419; Limayem et al., 2007: 710). Habit generally emerges from a specific behaviour or use of technology due to prior learning and because of previous experiences with the technology (Venkatesh et al., 2012: 161). As the performance of a task becomes more habitual, the less choice is needed and the influence of external factors on consumers' usage behaviours diminishes (Miladinovic & Xiang, 2016: 24).

Prior research has theoretically and empirically validated the inclusion of habit as a key predictor in adoption and acceptance behaviour research, including the adoption of mobile apps (e.g. Gupta et al., 2018: 145; Mutlu & Der, 2017: 179; Tak & Panwar, 2017: 248) and mobile shopping apps (e.g. Chopdar & Sivakumar, 2020: 42; Lee et al., 2019: 1; Miladinovic & Xiang, 2016: 45; Phang et al., 2018: 18; Van Niekerk, 2020: 269). Contextually, research relating to same-day delivery apps is limited. However, related literature theorises the interrelationship between habit and behavioural intention in the adoption of on-demand services, or food delivery services and/or apps (Erwanti et al., 2018: 9; Flores & Castaño, 2020: 38; Lee et al., 2019: 9; Rasli et al., 2020: 685).

From the widely reported interrelationship between habit and behavioural intention, it was concluded that as individuals become accustomed to and content with using food delivery apps, the chances of the action or activity being repeated and becoming an occurrence of habit increase. Such behaviour gradually evolves into habit, where users find that they must use mobile shopping apps in their daily or weekly routines. It was resolved and proposed that habit will have the same

significant influence on consumers' behavioural intention to continue using same-day delivery apps in a South African context.

7.3.1.4.7 Conclusions about the price value construct

Price value is described as the cognitive trade-off consumers make between the perceived benefits they will gain from using technology and the monetary cost involved in using it (Venkatesh et al., 2012: 161). Individuals would look for greater benefits in comparison to the monetary sacrifice (Gupta et al., 2018: 58). Contextually, certain monetary costs are involved with using same-day delivery apps, such as an Internet data bundle, a service and/or delivery fee charged by the operator, retailer or restaurant and a voluntary gratuity for the driver. The costs involved in using these types of apps might impede consumers' intentions to use them.

From the literature discussion provided in Chapter 4, section 4.2.8, it was concluded that price value significantly influences consumers' intention to adopt mobile shopping apps and on-demand mobile service platforms (e.g. Chopdar et al., 2018: 117; Erwanti et al., 2018: 9; Flores & Castaño, 2020: 38; Rasli et al., 2020: 679; Saad, 2021: 535; Tak & Panwar, 2017: 12). The theoretical interrelationship evident in the literature provided validation for the inclusion of price value in the proposed conceptual model. It was concluded and proposed that price value will play a decisive role in consumers' acceptance of same-day delivery apps in a developing country, such as South Africa, with a low disposable income market, high data costs and a high unemployment rate (Thusi, 2018: 57).

7.3.1.4.8 Conclusions about the lifestyle compatibility construct

Lifestyle compatibility refers to the alignment of lifestyle choices and values and is described as the degree to which individuals perceive that a particular technology is well suited to the way they think, act and lead their lives (Boateng et al., 2016: 471). Same-day delivery apps are argued to be compatible with a consumer's lifestyle if the user perceives the app to fit in with the way they live and conduct themselves socially. As a result, in the context of the research study, lifestyle compatibility was described as the beliefs and values that an individual holds about shopping online, and how well the activity of shopping online fits into the consumer's lifestyle (Cuna, 2020: 9).

Theory dating back to the advent of social cognitive theory (SCT) (Bandura, 1986) suggests that personal factors, behaviours and an individual's surroundings, such as lifestyle, is a key contributing factor in the adoption of new technological innovations (Belanche et al., 2020: 14;

Leung & Chen, 2017: 1639). Prior academic research provides supporting literature and empirical evidence of a noteworthy interrelationship between lifestyle compatibility and consumers' intention to use m-commerce platforms, mobile shopping apps and food delivery apps specifically (e.g. Arora & Malik, 2020: 98; Belanche et al., 2020: 14; Boateng et al., 2016: 468; Chawla & Joshi, 2017: 410; Shankar & Kumari, 2016: 14; Yang et al., 2021: 1).

The following conclusions were drawn from the literature discussion on lifestyle compatibility, relevant to the context of the research study:

- Individuals tend to adopt technologies and services that are compatible with their values, norms, past experiences and self-perception (Belanche et al., 2020: 14; Leung & Chen, 2017: 1639).
- The compatibility of mobile apps with individuals' lifestyles has become increasingly significant since numerous competing technological innovations are available to consumers to choose from.
- Individuals tend to search for alternative solutions to make everyday tasks easier and suited to their lifestyles (Belanche et al., 2020: 1).
- Home-delivery services, such as same-day or on-demand delivery apps, are convenient for online shoppers (Chen et al., 2014: 69), and consumers seek quick and convenient meals during or after a busy workday (Chai & Yat, 2019: 63).
- Due to the busy pace of life and the opportunity to discover and reach more restaurants and retailers, home delivery services have become even more valuable to consumers (Belanche et al., 2020: 1; Chai & Yat, 2019: 63).

From the literature discussion, and due to the many competing mobile shopping apps available to consumers, it was concluded and proposed that the compatibility of same-day delivery apps with an individual's lifestyle would be paramount and was therefore considered to be a potential significant contributing factor in the acceptance of same-day delivery apps in a South African context.

7.3.1.4.9 Conclusions about the perceived risk construct

Irrespective of the exponential growth of the mobile app market, technology presents various security and privacy challenges deterring the adoption of online shopping platforms (Belanche et al., 2020: 6). Perceived risk and security have received a great deal of attention in the literature

as factors that influence users' acceptance of new technological platforms, systems and devices. The inclusion of the construct was therefore warranted in the research study.

Contextually, perceived risk referred to the potential loss as perceived by a customer while shopping online using mobile retail apps when compared to purchasing products offline (Kaushik et al., 2020: 12). A vast body of literature theorises that there is a noteworthy interrelationship between perceived risk and the intention to adopt or use a new technological platform or device.

Prior research in the context of mobile shopping apps affirms a negative association between perceived risk and intentions towards online purchasing in various sectors, including retailing (Alaimo et al., 2020: 3; Arora & Malik, 2020: 106; Kaushik et al., 2020: 12; Marriott & McLean, 2019: 106) and m-commerce research (Ali & Maideen, 2019: 375; Kaushik et al., 2020: 12; Marriott & McLean, 2019: 19; Vasileiadis, 2014: 187; Verkijika, 2018: 1673). Research related to same-day, or on-demand delivery apps, is scant, but Alaimo et al. (2020: 1), Belanche et al. (2020: 6) and Pauzi et al. (2017: 1) affirm the significance of perceived risk in the adoption of online food delivery services, purchasing groceries online and the adoption of online food shopping during the COVID-19 pandemic. As a result, it was concluded and proposed that there is an inverse relationship between consumers' perceived risk and behavioural intention, suggesting that individuals with high perceived risk are more likely to avoid mobile shopping apps and choose offline shopping as their preferred medium to shop (Kaushik et al., 2015: 22).

The following conclusions were drawn from the literature discussion on perceived risk, pertinent to the research study:

- Perceived risk is more prevalent in online shopping platforms because of the spatial separation between the seller and the consumer (Gupta et al., 2018: 54).
- Online shoppers could be discouraged by various risks and security concerns, such as the potential loss of control over personal data, such as credit card detail, physical address and contact information, concerns that personal data might be misused, concerns that mobile transactions will result in transaction fraud, the inability to inspect products before purchasing them, such as concerns about the quality or freshness of products and not being able to judge the size, texture, or colour of the product, the risk of having a stranger delivery the order to their home and having physical contact with the driver, the waiting time for products to arrive and the lead time for complaints or returns to be addressed by the retailer (Dawi, 2019: 117; Pauzi et al., 2017: 5, Van Niekerk, 2020: 32).

- Same-day delivery apps may involve a high risk of privacy violations as users' personal information, such as their contact details, location information and payment information, must be disclosed and can be compromised.
- Perceived risk acts as an obstacle for consumers when it comes to making purchases through a mobile shopping channel (Van Niekerk, 2020: 148), such as same-day delivery apps.

7.3.1.4.10 Conclusions about the perceived self-efficacy construct

To address the limitation reasoned by Moghavvemi et al. (2013: 247) that the UTAUT2 fails to measure individual characteristics towards behavioural intention to adopt technology, perceived self-efficacy was included in the conceptual model. Contextually, perceived self-efficacy implied an individual's belief or perception in their own abilities and self-confidence to complete a specific activity or task using mobile apps (Hu & Zhang, 2016: 645; Yul, 2014: 12).

A theoretical interrelationship between perceived self-efficacy and behavioural intention is widely reported in the literature, supported by empirical evidence. Prior empirical findings confirm that self-efficacy implicitly affects consumers' intention to adopt various types of mobile apps (Alalwan et al., 2016: 690; Jeong & Yoon, 2013: 1; Makki et al., 2016: 454; Singh et al., 2018: 121; Wei et al., 2020: 1), including the adoption of on-demand goods delivery apps (Elango et al., 2019: 13). Grounded in theoretical validation, a significant interrelationship between perceived self-efficacy was expected and proposed to influence consumers' behavioural intention to continue using mobile apps, including same-day delivery apps.

The following conclusions were drawn from the literature discussion on perceived self-efficacy:

- Perceived self-efficacy allows an individual to perform the intended task on a mobile app more successfully (Gitau & Nzuki, 2014: 91).
- The more self-efficacious users view themselves to be, the higher their intention to use technology will be (Okumus & Bilgihan, 2014: 39; Marriott et al., 2017: 576).
- Individuals with higher expertise will have heightened intentions to use a system than an individual with lower expertise (Jeong & Yoon, 2013: 35).
- If users believe that they have the required personal knowledge, skills and/or abilities to use certain mobile apps, their intention to use them will increase (Luarn & Lin, 2005: 878).

- Individuals with high perceived self-efficacy are more likely to adopt m-commerce as they expect the system to be user-friendly and easy to use, and it is therefore expected that these individuals will use m-commerce more incessantly (Islam et al., 2011: 82).

7.3.1.4.11 Conclusions about the attitude towards use construct

Due to the UTAUT2 Model being criticised because individual characteristics were not considered in the development of the model, attitude towards using technology was investigated as a salient factor influencing consumers' behavioural intention towards using same-day delivery apps. Contextually, consumer attitudes refer to "… the consistent tendency of consumers to behave, favourably or unfavourably, with regards to a specific product or brand" (Schiffman & Kanuk, 2004: 253). Scholars have noted that understanding consumer attitudes is critical in that it enables marketers to predict consumers' behaviours (Makanyeza, 2014: 874).

The influence of the attitudinal construct on behavioural intention has been widely researched in the e-commerce and m-commerce domains (e.g. Al-Debei et al., 2013: 46; Heirman & Walrave, 2012: 614; Sanne & Wiese, 2018: 4). Research pertaining specifically to the interrelationship between the attitude towards use and behavioural intention related to same-day delivery apps could not be found. However, related literature provides supporting evidence that a consumer's attitude towards using a new technology would significantly predict their intention to use it (e.g. Cho et al., 2018: 108; Lee et al., 2017: 1468; Shukla & Sharma, 2018: 192; Troise et al., 2021: 675). Numerous studies have found a strong empirical relationship between attitude and behavioural intention and consequently, the more positive the attitude towards certain behaviour, the more likely the individuals are to form an intention to perform the given behaviour (Al-Debei et al., 2013: 46; Heirman & Walrave, 2012: 614; Sanne & Wiese, 2018: 4). As a result, it was concluded and proposed that attitude towards use is a potential predictor of behavioural intention and was included as a salient factor in the proposed conceptual model.

7.3.1.5 Literature research objective 5

The fifth literature research objective was formulated as follows:

Research objective 5:	To identify and conceptualise the moderating constructs (generational cohort and gender) and investigate their effect on the independent constructs and behavioural intention.

Specific literature research objective 5 was addressed in Chapter 4, section 4.2.13, in which the moderators were identified and contextualised to a South African consumer market, and the theoretical effects on the relationship between the various independent constructs and the dependent construct were investigated in the literature.

Moderators were investigated as other research suggests that the UTAUT2 Model should be tested with the inclusion of demographic factors, as individuals are likely to differ substantially from each other in terms of their beliefs, values, perceptions, or their understanding of different constructs (Ameen & Willis, 2018: 2; Trojanowski & Kutak, 2017: 97-98). Failure to examine the impact of heterogeneity may therefore result in drawing incorrect conclusions and formulating invalid recommendations (Hair et al., 2012: 427; Trojanowski & Kutak, 2017: 97-98). In the UTAUT2 Model, three moderators were measured, namely age, gender and experience. Experience was not observed in this research study since grocery-related same-day delivery apps were still in their infancy in the South African market at the time the study was conducted, and experience with these apps may have been limited. In addition, the data used in the research study were cross-sectional rather than longitudinal. Consequently, only generational cohort (age) and gender as moderators were investigated.

Chapter 4, section 4.2.13.1, contextualised the generational cohorts relevant to the South African consumer market. The following conclusions were taken from the literature pertaining to the generational cohorts relevant to the South African market:

- There is a lack of consensus about the generational cohorts in South Africa, but defining moments in South African history, compared to Western societies, have been identified by Viljoen et al. (2018: 5) and were adopted in the research study.
- South Africa's history has been defined by several events and profound political and societal transformation that demarcated each generation (Bevan-Dye, 2016: 12; Katherman, 2016; Padayachee, 2017: 60; Viljoen et al., 2018: 2), for instance:
    - Baby Boomers (born between 1950 and 1969) were defined by the Black Consciousness Movement, an anti-apartheid movement that emerged in South Africa in the mid-1960s with the jailing and banning of the ANC and Pan Africanist Congress leadership after the Sharpeville Massacre in 1960.
    - Generation X (born between 1970 and 1989) was marked by apartheid, political violence, economic instability and economic sanctions.
    - Generation Y (born between 1990 and 2000) grew up during the transitional post-apartheid era with more education and employment opportunities.

- Generation Z, also known as the Zoomers (born between 2001 and 2015), would be characterised by the born-free generation in South Africa, who were born after the dawn of democracy in South Africa. Members of Generation Z are characterised as being more technologically innate and able to use multiple technological systems and devices.
- Generation Alpha (born between 2016 and 2020) grew up during a time of terrorism, war, gender equality and the global pandemic (COVID-19).

- Technology shapes the behaviours of individuals born in specific eras and is one of the factors that may affect individuals' intention to use an information system (Gafni & Geri, 2013: 20). The leading technology during each era and the generation's attitude and adoption behaviour of new technologies were detailed in Chapter 4, section 4.2.13.1.2.

The effect of generational cohort and gender on the relationship between the identified independent constructs and behavioural intention was supported by prior research (refer to Chapter 4, section 4.2.13). The theoretical interrelationship between all observed constructs was discussed in detail in Chapter 4, section 4.2.13.4. The literature provides supporting evidence that generational cohort and gender theoretically moderate the relationship between the 11 independent constructs and consumers' behavioural intention to continue using same-day delivery apps.

7.3.1.6 Literature research objective 6

The last literature research objective of the study was as follows:

Research objective 6:	To develop a conceptual model based on the theoretical relationship dynamics between the independent constructs, the moderating effects and behavioural intention.

Building on the literature review and identified independent constructs, Chapter 4 (section 4.3) presents the proposed conceptual model (see Figure 4.1). The conceptual model addresses specific literature research objective 6 by capturing the interrelationships found in past research and empirical results.

It was theorised that the 11 identified independent constructs are significantly related to behavioural intention such that they will influence South African consumers' intention to continue

using same-day delivery apps. The research study espoused the main effects of the UTAUT2 Model as the foundational theory in measuring consumers' behavioural intention to continue using same-day delivery apps in a South African context. The research study furthermore built on the UTAUT2 Model by incorporating four additional exogenous mechanisms to determine their significance on consumers' behavioural intention to continue using same-day delivery apps in a South African context. These exogenous mechanisms comprised lifestyle compatibility, perceived risk, perceived self-efficacy and attitude towards use. Theoretical justification was provided for the inclusion of the abovementioned constructs in the context of the research study, thereby extending the UTAUT2 Model with four additional constructs or exogenous mechanisms.

To furthermore contribute to the predictive and explanatory power of the UTAUT2 Model, the inclusion of two moderators, namely generational cohort (age) and gender, was theorised to affect the relationship dynamics between the 11 independent constructs and behavioural intention. Significant differences between generational cohort and gender have widely been reported in the literature (refer to Chapter 4, section 4.2.13.4).

The next section addresses conclusions regarding the empirical research objectives of the research study.

7.3.2 CONCLUSIONS REGARDING THE EMPIRICAL STUDY

The following sections focus on the conclusions drawn from the empirical results and analysis reported in Chapter 6. The conclusions are presented in accordance with the secondary empirical research objectives as set out in Chapter 1 (section 1.5) and section 7.2 above. First, a summary of the biographical profile of respondents who participated in the research study is given.

7.3.2.1 Demographic profile of respondents

The research instrument was administered via a self-administered, online questionnaire to a diverse group of consumers residing in Gauteng, KwaZulu-Natal or the Western Cape province of South Africa. Respondents were required to be acquainted with smartphones and use same-day delivery apps regularly (weekly), whether it be directly from a grocery store or a food outlet's app, or through a third-party intermediary app, such as Uber Eats or Mr D Food. A non-probability convenience sample of 485 usable questionnaires was returned, yielding a response rate of 4.85%. The sample size was considered suitable for achieving adequate statistical analyses.

The biographical profile of respondents comprised 69.5% females, 29.9% males and 0.6% who preferred not to say. Most (62.9%) respondents were between the ages of 25 and 40. In respect of generational cohorts, 54.2% were born between 1990 and 2000 (Generation Y), 36.5% were born between 1970 and 1989 (Generation X), 5.4% were born between 2001 and 2003 (Generation Z) and 3.9% were born between 1950 and 1969 (Baby Boomers). Most (60%) respondents resided in Gauteng, followed by KwaZulu-Natal (21.9%) and then the Western Cape (17.9%).

The subsequent sections address the seven empirical research objectives which were formulated for the research study.

7.3.2.2 Empirical research objective 1

The first empirical research objective for the study was as follows:

Research objective 1:	To explore consumers' use of same-day delivery apps to establish their relevance in the South African consumer market.

The first empirical research objective was achieved in Chapter 6, section 6.2.2. Consumers' use of same-day delivery apps was explored by assessing participants' use of online technologies and/or platforms, specifically their use of same-day delivery apps. Furthermore, the reasons for using same-day delivery apps were explored to establish their use and relevance in the South African market.

The research confirmed widespread adoption of online technologies and platforms, suggesting a crucial online presence for retailers and restaurants. Specifically, food delivery apps like Debonairs Pizza and Mr D Food saw frequent use, highlighting their established role in the market. However, grocery-related same-day delivery platforms, such as Checkers Sixty60 and Woolies Dash, showed lower penetration. This can be attributed to several factors. Firstly, the infancy of same-day delivery apps in the South African market, as the major grocery-related same-day delivery services only began in 2020, while the research study was conducted in 2021. Secondly, consumers' limited knowledge of same-day delivery apps and/or, thirdly, the inadequate reach of same-day delivery apps in the market as the apps were only offered by a few selected participating retailers in major business hubs, such as Cape Town, Johannesburg, Durban, La Lucia, Pretoria and Sandton (Wagner, 2019; WHL, 2020).

To reiterate, it should be borne in mind that data were collected during the worldwide COVID-19 pandemic and the civil unrest which took place in KwaZulu-Natal and Gauteng in 2021 (Business Tech, 2021a; The Economist, 2021; The Presidency, 2021). The pandemic and the civil unrest gave rise to the implementation and use of same-day delivery apps as, presumably, consumers felt safer purchasing by means of these apps as opposed to physically visiting a store or restaurant. The results support this assumption as respondents indicated convenience, safety and social distancing as the main reasons for using same-day delivery apps. Same-day delivery apps not only provided consumers with the convenience of having products delivered to their door, but also allowed users to maintain social distancing during the COVID-19 pandemic, avoid public places and refrain from entering areas where violent riots took place. It can be argued that the COVID-19 pandemic and socio-economic challenges in South Africa have provided a catalyst for retailers to accentuate the importance of using same-day delivery platforms.

The results presented in Chapter 6, section 6.2.2, provide supporting evidence for empirical research objective 1. Overall, the results suggest that same-day delivery apps have value in the South African consumer market as these apps were often used by respondents. Retailers and/or restaurant owners could benefit from adopting a same-day delivery business model to reach the wider South African market demanding quicker delivery times.

7.3.2.3 Empirical research objective 2

The second empirical research objective was as follows:

Research objective 2:	To explore the suitability of the individual items measuring the latent constructs in the research instrument involving a sample of South African consumers.

In Chapter 6, section 6.3, the second empirical research objective, focusing on exploring the suitability of individual items measuring latent constructs in the research instrument with a sample of South African consumers, was successfully accomplished. This analysis involved assessing the average mean and standard deviation scores for each individual item used to measure the 11 independent constructs and the dependent construct in the research instrument. This examination was conducted to isolate, and the conclusions drawn from the results aimed at evaluating the suitability of these individual items, without implying any specific direction or relationship with the dependent variable.

The findings from the descriptive results of the independent and dependent variables led to several noteworthy conclusions. On average, respondents expressed agreement with statements measuring various factors influencing consumers' behavioural intention to continue using same-day delivery apps, indicating that the individual scale items were meaningful to a sample of South African consumers. Respondents affirmed the time-saving benefits, ease of use, and explicitness of utilising same-day delivery apps. Consumers' attitudes toward the influence of interpersonal influencers, the enjoyment derived from using the apps, and the perception of habitual use were generally positive. Overall, respondents demonstrated favourable attitude, satisfaction and commitment towards the continued use of same-day delivery apps.

However, there was some neutrality observed in respondents' views regarding the impact of interpersonal influencers, potential addiction to same-day delivery apps, and the comparison of costs between using the apps and physically going to a store. On average, respondents maintained a somewhat objective stance concerning the influence and persuasion exerted by interpersonal influencers, such as friends and family, on their decision to continue using same-day delivery apps. This impartiality was attributed to demographic differences, with research suggesting that women tend to be more perceptive towards others' opinions and prefer social interactions when forming intentions to use new technologies (Lee et al., 2017: 566). Moreover, Onwona-Agyman (2019: 7) believes that older individuals are more likely to rely on their social support network when they have less experience with the specific technology.

On the topic of habituality, respondents, on average, agreed that same-day delivery apps had become habitual, with frequent usage. However, there was a degree of impartiality regarding whether they were addicted to these apps. The impartiality could be attributed to consumers' reluctance to accept that they were addicted to using a shopping app, as the term could have had a negative connotation.

In terms of costs, respondents, on average, agreed that the benefits offered by using same-day delivery apps outweighed the associated monetary costs. However, there was neutrality regarding whether purchasing products through same-day delivery apps was more expensive than physically going to the store. The impartiality could be attributed to the fact that the cost of using a same-day delivery app cannot be weighed up against physically visiting a store, as different factors are at play. For instance, the use of same-day delivery apps involves data costs, service fees and delivery fees, whereas the costs associated with physically visiting a store include transportation cost and time.

From the descriptive results presented in Chapter 6, section 6.3, and the conclusions provided above, it was resolved that the individual scale items in the research instrument are significant to a South African consumer sample. Participants, on average, agreed with all the statements in the scale, and the data exhibited normal distribution with acceptable skewness and kurtosis values. Consequently, empirical research objective 2 was successfully achieved, indicating that the individual scale items in the research instrument appeared suitable for measuring the 11 independent variables and the dependent variable within the South African consumer context.

7.3.2.4 Empirical research objective 3

The third empirical research objective for the study was as follows:

Research objective 3:	To assess the validity of the proposed measurement model for the collected data from a sample of South African consumers in order to determine if the model adequately measures the construct of behavioural intention.

The third empirical research objective was achieved in Chapter 6, section 6.4.1. To assess the validity of the proposed measurement model, CFA was conducted by first assessing the measurement model's fit and, second, assessing the reliability and validity of the measurement model through construct validity.

An investigation of the measurement model's fit indices revealed that the observed data poorly represented the latent constructs of interest. Despite acceptable CMIN/df (2.801) and RMSEA (0.061) values, other indices like GFI (0.68), AGFI (0.65), NFI (0.73), TLI (0.80) and CFI (0.81) indicated a mediocre to poor fit with the observed data, preventing the establishment of the measurement model's validity (refer to Table 6.17 in section 6.4.1.1). Further exploration of the construct validity involved assessing composite reliability and using the average variance extracted (AVE) method. While composite reliability met recommended thresholds (≥ 0.70; Hair et al., 2011: 140; Hamid et al., 2017: 2; Lin et al., 2020: 3), AVE values were unacceptable for eight of the twelve observed constructs, (eleven independent constructs and the dependent construct), casting doubt on the validity of both individual variables and constructs in the measurement model (refer to Chapter 6, section 6.4.1.2.1 and Table 6.18). Discriminant validity, assessed using the heterotrait-monotrait (HTMT) criterion revealed a lack of distinctiveness among observed constructs, refuting the discriminant validity of the measurement model (refer to Chapter 6, section 6.4.1.2.2 and Table 6.19).

From the empirical results indicating mediocre model fit, unsatisfactory convergent validity and the lack of discriminant validity, it was concluded that the proposed conceptual model presented in Chapter 4 (Figure 4.1) did not fit the data well and modifications to the measurement model were required.

The outcomes of the CFA conducted in Chapter 6, section 6.4.1, yielded several noteworthy conclusions:

- Several hypotheses, integral to the development of the conceptual model, faced empirical challenges due to inadequate model fit indices and a lack of convergent and discriminant validity. Consequently, the significance of factors such as performance expectancy, effort expectancy, facilitating conditions, habit, price value, lifestyle compatibility, perceived self-efficacy and attitude towards use could not be statistically explored as influential factors shaping consumers' behavioural intention to continue using same-day delivery apps. This finding stands in contrast to the assertions of several researchers who have underscored the significance of these factors in technology adoption research (e.g. Belanche et al., 2020: 1; Chopdar & Sivakumar, 2019: 46; Elango et al., 2019: 12; Karulkar et al., 2019: 156; Khurana & Jain, 2019: 757; Rasli et al., 2020: 685; Saad, 2021: 535; Sair & Danish, 2018: 501; Soni et al., 2019: 369; Van Niekerk, 2020: 270; Zhao & Bacao, 2020: 4) (also refer to Chapter 4, section 4.2).
- The absence of discriminant validity among the above constructs, in the context of this South African research study, was attributed to the evolution of the Internet and mobile technologies. The familiarity of consumers with various mobile technologies, their adeptness in using mobile devices, possession of necessary and infrastructure, and positive perceptions of mobile shopping apps contribute to this lack of distinction. Consumers' connectivity, adaptability to change, and openness to new technology empower them to quickly learn and independently resolve related problems, supported by the integration of mobile apps into their daily lives. This familiarity extends to various technologies, enhancing their capability to understand and comfortably use same-day delivery apps with confidence, skills, knowledge and resources.
- Social influence (hypothesis 4) and perceived risk (hypothesis 9) emerged as the only observed constructs with acceptable convergent and discriminant validity.
- The foundational theory on which the conceptual model was built – the UTAUT2 Model – was found to be largely irrelevant in the context of the research study, with the exception of social influence. This contradicts the prevailing view among many researchers who advocate

for the suitability of the UTAUT2 Model in determining acceptance and use behaviours across diverse technological systems, devices and/or platforms.

- The initial CFA results (discussed in Chapter 6, section 6.4.1) refuted the conceptual model presented in Chapter 4 (Figure 4.1), necessitating modifications to the measurement model to better align with observed data.

In response to the results obtained from the CFA applied to the original measurement model, corrective measures were implemented to formulate an improved measurement model that more adequately fit the data. The revised model retained two of the original observed independent constructs, namely social influence and perceived risk. Additionally, a third independent variable emerged from the dataset, as various scale items' factor loadings clustered under a new latent variable, termed 'perceived customer value'.

The revised measurement model was also subjected to an assessment of the goodness-of-fit indices, and reliability and validity assessment, to establish whether the revised measurement model more adequately fit the data. The revised measurement model was considered to have satisfactory goodness-of-fit indices and appeared to fit the data well (see Chapter 6, section 6.4.2.1 and Table 6.21). Furthermore, a thorough examination of composite reliability and AVE was conducted, affirming the convergent validity of the revised measurement model. Acceptable composite reliability and AVE scores were observed for each of the independent construct and the dependent construct, emphasising the model's reliability (refer to Chapter 6, section 6.4.2.2 and Table 6.22). Discriminant validity of the revised measurement model was explored using the HTMT criterion, which fell within the stringent recommended validity threshold (≤ 0.85) (refer to Chapter 6, section 6.4.2.2 and Table 6.23).

The following conclusions were drawn from the results related to the revised measurement model presented in Chapter 6 (Figure 6.3):

- In comparison to the initial conceptual model theorised and presented in Chapter 4 (Figure 4.1), only two independent constructs remained significant, namely social influence and perceived risk, although some scale items were removed to improve the validity of the model (refer to Chapter 6, section 6.4.1.3 and Table 6.20).

- A latent construct, termed perceived customer value, emerged from the clustering of several scale items. This construct was contextualised as the overall assessment of consumers towards product or service utility based on varied benefits and sacrifices (Zeithaml, 1988 in Chahal & Kumari, 2012: 168). Perceived customer value captures the trade-off between the

perceived benefits and the perceived sacrifices (Hsu & Lin, 2015: 48). The remaining scale items resembled the notion that same-day delivery apps increase the user's productivity, enabling the user to do things that are important, they are easy to use, a good idea and cost-effective. Consequently, it was inferred that the benefits and satisfaction derived from using same-day delivery apps outweigh the associated sacrifices, as indicated by the overall concept of perceived customer value.

With favourable goodness-of-fit outcomes and validated convergent and discriminant validity in the revised measurement model, empirical research objective 3 was successfully achieved. The refined measurement model highlights three central independent constructs – namely social influence, perceived risk and perceived customer value. These constructs are deemed potential predictors of consumers' behavioural intention to continue using same-day delivery apps within a South African context. Subsequent to this, additional statistical analyses were conducted on the revised model.

7.3.2.5 Empirical research objective 4

The fourth empirical research objective, as stated below, was determined based on the revised measurement model.

Research objective 4:	To examine the correlation (direction and strength) between the measurement model's independent variables and behavioural intention, as manifested in a sample of South African consumers.

Research objective 4 was achieved in Chapter 6, section 6.6.1, in which correlation analysis was conducted to examine the proportions of the model's independent variables and behavioural intention. Pearson's product-moment correlation coefficient (symbolised as *r*) was used to assess the strength and direction of the linear association between the independent variables (social influence, perceived risk and perceived customer value) and the dependent variable (behavioural intention). Cohen's guidelines (1988) pertaining to Pearson's *r* were implemented in interpreting the correlation coefficient results.

The outcomes revealed significant linear associations ($p \leq 0.05$) from Pearson's correlation coefficient results (refer to Chapter 6, Table 6.25). Upon examining the specifics, heightened social influence exhibited a positive correlation with increased levels of behavioural intention ($r = 0.482$; medium effect). This signifies that individuals, influenced by the suggestions,

comments, reviews and posts of significant others and other users, are more inclined to continue using a specific shopping app (Naqvi et al., 2020: 4; Malik et al., 2017: 107).

Conversely, an increased perceived risk demonstrated a small negative correlation with behavioural intention (r = -0.115; small practical effect). Accordingly, if the risks associated with using same-day delivery apps are perceived to be too high and pose too many uncertainties, individuals will have lower intentions to continue using same-day delivery apps. On the contrary, if same-day delivery apps pose few risks to users, they will present with heightened intentions to continue using these apps. Scholars have acknowledged that one of the main factors discouraging individuals from using online platforms or mobile shopping apps is their concern about privacy and security (risk factors) (e.g. Chopdar et al., 2018: 3; Hubert et al., 2017: 181; Kaushik et al., 2020: 12).

Furthermore, a substantial positive correlation was observed between perceived customer value and behavioural intention (r = 0.773; large practical effect), indicating that heightened perceived customer value is associated with increased intention to continue using same-day delivery apps. Thus, if the value users receive from using same-day delivery apps offset the losses associated with using the apps, individuals will have increased intentions to use these apps. Prior research supports the correlation between perceived customer value and behavioural intention (e.g. Khan & Kadir, 2011: 4094; Mahendar, 2017: 100; Zhang et al., 2021: 29). Perceived value simultaneously integrates customers' perception of the benefits received and the sacrifices involved in using the technology (Jen et al., 2011: 326), and is therefore highly associated with usage intention (Mahendar, 2017: 89).

From the above conclusions, empirical research objective 4 was effectively achieved, as discernible correlations were identified between the independent variables (social influence, perceived risk and perceived customer value) and behavioural intention. Positive correlations were evident between social influence as well as perceived customer value with behavioural intention, while a small negative correlation was noted between perceived risk and behavioural intention.

7.3.2.6 Empirical research objective 5

As the initial measurement model was discredited in Chapter 6, section 6.4.1, due to the lack of discriminant validity, unsatisfactory convergent validity and unacceptable model fit indices, a revised measurement model emerged from the data (see Chapter 6, Figure 6.3). For this reason, empirical research objective 5 was achieved by considering the interrelationships between the

variables of the revised measurement model discussed in Chapter 6, section 6.4.2, namely social influence, perceived risk and perceived customer value.

The fifth empirical research objective of the study was as follows:

Research objective 5:	To evaluate the relationships between the empirically manifested variables to construct a statistically significant structural model.

SEM was performed to evaluate multivariate relationships between the elements of the empirically manifested latent variables to construct a statistically significant structural model (empirical research objective 5). Parameter estimates and path coefficients were assessed to determine the significance and direction of the relationship and establish the amount of variance the independent variables have on the dependent variable. The structural model that emerged from the data is shown in Chapter 6 (Figure 6.11).

The SEM analysis yielded the following key conclusions: Firstly, the structural model accounted for a substantial 70.8% ($R^2 = 0.708$) of the variance in behavioural intention. Secondly, while social influence ($p = 0.651$) and perceived risk ($p = 0.585$) exhibited statistically insignificant relationships with behavioural intention, a significant positive relationship was observed between perceived customer value and behavioural intention ($p \leq 0.01$) (see Chapter 6, Table 6.26). Thirdly, in terms of relative importance, perceived customer value emerged as the primary explanatory factor, explaining 85.7% of the variance in behavioural intention. Consumers' acceptance to continue using same-day delivery apps was mostly influenced by their perception of whether the benefits outweighed the sacrifices. The literature supports the interrelationship, stating that a customer's overall assessment of a product and/or service, such as a same-day delivery app, is based on the benefits received from using the mobile app compared to the sacrifices they must make to be able to use the mobile app to its fullest extent (Chahal & Kumari, 2012: 168; Hsu & Lin, 2015: 48). It is therefore concluded that consumers would continue using same-day delivery apps if the benefits they derive from using these apps offsets the losses, such as the service and delivery fee involved in using the apps.

Furthermore, consumers consider the productivity of the apps, the ease of using it, the fun and excitement derived from using the apps and their cost-effectiveness as the benefits resulting from using same-day delivery apps. This aligns with established research correlating perceived customer value with various elements, including price, quality, sacrifice and satisfaction (Chang & Dibb, 2012: 256). Consumers generally decide to purchase a product, or in this case use a mobile

app, after considering multiple consumption values, such as gratification, quality, the cost-effectiveness and their trade-offs (Jansri, 2018: 1).

Following the SEM analysis, hypotheses and a revised conceptual model were presented in Chapter 6 (Figure 6.12). Hypotheses related to social influence (H_a1), perceived risk (H_a2), perceived customer value (H_a3), and the moderating effects of generational cohort and gender (H_a4) were systematically tested. The results demonstrated that social influence and perceived risk did not emerge as statistically significant predictors of behavioural intention ($p \geq 0.05$), leading to the rejection of corresponding hypotheses (H_a1 and H_a2). Perceived customer value, however, contributed significantly to explaining the percentage of variance in behavioural intention ($R^2 = 0.857$), supporting H_a3. High levels of perceived customer value are therefore associated with high levels of behavioural intention. As stated in Chapter 6, the significance is attributable to consumers' overall assessment of products and/or services based on the varied benefits and sacrifices (Chahal & Kumari, 2012: 168). Typically, individuals would offset the sacrifices they must make to use same-day delivery apps with the benefits they will receive from using these apps. If the benefits are considered pleasing, customers will be willing to sacrifice any losses associated with using the apps. The variance could be attributed to consumers placing more emphasis on the benefits offered by same-day delivery apps, compared to the disadvantages involved in using these apps, because of the COVID-19 pandemic and the civil unrest, which was imminent in South Africa at the time of data collection. It can be presumed that consumers would rather pay the service and delivery fee involved in using same-day delivery apps than risk contracting the virus or entering areas where violent protests took place.

The moderation analysis for H_a4 is addressed in section 7.3.2.7 below.

Empirical research objective 5 was thus successfully achieved through the development of a reliable and valid structural model, providing valuable insights into the complex relationships influencing consumers' behavioural intention to continue using same-day delivery apps.

7.3.2.7 Empirical research objective 6

The sixth empirical research objective was as follows:

Research objective 6:	To empirically assess the interaction effects between the independent variables and the dependent variable, and two demographic conditions (moderators), namely generational cohort and gender.

Research objective 6 was successfully achieved in Chapter 6, section 6.6.3. Regression-based moderation analysis was conducted to assess whether the effect of the independent variables – social influence, perceived risk and perceived customer value – on the dependent variable were conditional upon consumers' disposition in terms of their age (generational cohort) and gender. The purpose was to determine whether the significant pathways identified in the SEM analysis were conditional upon age and gender.

The following conclusions were drawn from the results of the moderation analysis discussed in Chapter 6, section 6.6.3 (Tables 6.27 to 6.30):

- The relationship between social influence and behavioural intention remained unaffected by consumers' generational cohort (age) or gender ($p \geq 0.05$). Although the finding is inconsistent with that of the UTAUT2 Model, it is in line with studies that have replicated the UTAUT2 Model in studying user adoption behaviours in various contexts (Daniali et al., 2022: 10; Leong et al., 2013a: 5614; Leong et al., 2013b: 2118; Maduku, 2015: 11; Terblanche & Kidd, 2022: 10).
- The influence of perceived risk on behavioural intention did not exhibit dependency on consumers' generational cohort (age) or gender, with results proving to be statistically insignificant ($p \geq 0.05$). This outcome contradicts the results of several studies that included demographic differences inherent in technology adoption (Aboobucker & Bao, 2018: 25; Ali & Maideen, 2019: 385; Marriott & Williams, 2018: 20; Wang, 2018: 201). Scholars have, however, reported similar findings in that gender and age have no moderating effect on the relationship between perceived risk and behavioural intention (e.g. Belanche, Guinalíu & Albás, 2022: 8; Terblanche & Kidd, 2022: 10).
- The relationship between perceived customer value and behavioural intention was conditional upon a consumer's gender ($p \leq 0.05$), with a stronger, albeit small, interaction effect observed for females (0.936) compared to males (0.759) (see Tables 6.27 and 6.28). Female consumers place more importance on the value derived from using same-day delivery apps than male consumers. Women are generally more attracted to uniqueness and exclusivity as attributes of products/services and are thus willing to pay higher prices to get these attributes (Stan, 2015: 1596). Stan (2015: 1596) argues that men are more task-oriented and tend to compromise less on lower prices. Consequently, the perceived value female consumers derive from using same-day delivery apps compensates for the sacrifice they must make to use the apps.

- The relationship between perceived customer value and behavioural intention was influenced by a consumer's generational cohort ($p \leq 0.05$), with a stronger interaction effect observed for the Baby Boomer and Generation X cohort (or the older cohort) (1950 – 1989) (0.977), compared to the Generation Y and Generation Z cohort (or the younger cohort) (1990 – 2003) (0.799) (see Tables 6.29 and 6.30). This implies that as perceived customer value increases, the intention to continue using same-day delivery apps rises more significantly for older consumers (Baby Boomers and Generation X). It could be inferred that Baby Boomers and Generation X-ers has limited funds due to perhaps being retired or nearing retirement, being more conscious about saving money, or having a family with children, and therefore the monetary sacrifice is higher than for the Generation Y and Z (younger) cohort. The benefits Baby Boomers and Generation X-ers receive from using same-day delivery apps must be worth the sacrifice, and consequently perceived value is more significant in their intentions to continue using same-day delivery apps.
- The moderating effect of gender and generational cohort on the interrelationship between perceived customer value and behavioural intention was considered trivial, with minimal R^2 change (R^2 change: 0.005 and 0.006).

A view of the model with accepted relationships indicated in red is presented in Figure 7.1. H_a1 and H_a2 were not supported, but H_a3 was. H_a4 was partially accepted as generational cohort and gender moderately impact the relationship between perceived customer value and behavioural intention.

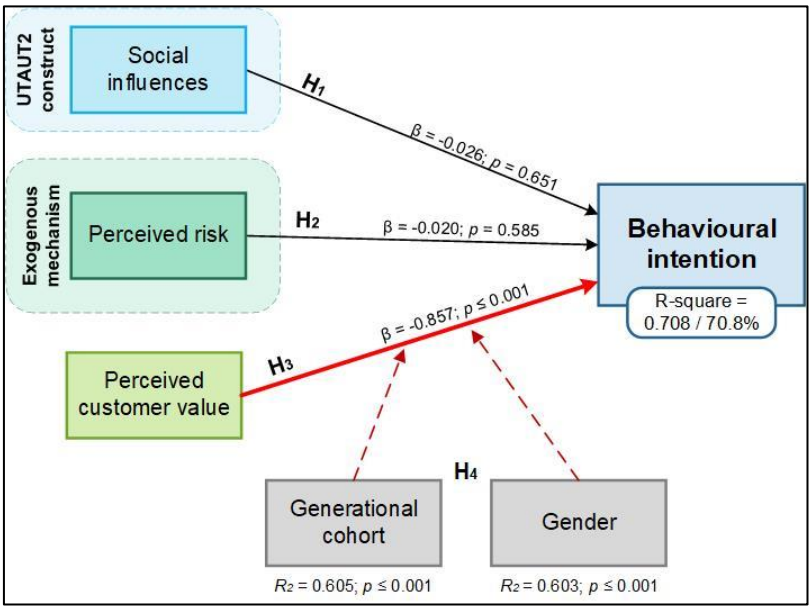

Figure 7.1: Model with accepted relationship (hypothesis)

Source: Author's own compilation

From the above conclusions it was confirmed that demographic factors (generational cohort and gender) as moderators, in the context of the research study, only marginally impact the relationship between perceived customer value and behavioural intention. The relationship between social influence and perceived risk, and the dependent variable (behavioural intention) are not moderated by gender and generational cohort. However, the relationship between perceived customer value and behavioural intention was moderated by gender and generational cohort, albeit small. The moderating hypothesis (H_a4) was consequently only partially accepted (*Generational cohort and gender significantly moderate the relationship between the independent variables and behavioural intention to continue using same-day delivery apps*). Empirical research objective 6 was therefore successfully achieved.

7.3.2.8 Empirical research objective 7

The seventh empirical research objective was as follows:

Research objective 7:	To assess whether there are significant differences between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps.

Research objective 7 was achieved in Chapter 6, section 6.6.4. Tests for significant group mean differences were explored to determine whether South African consumers from various demographic groups differ meaningfully in their behavioural intention to continue using same-day delivery apps. Group differences were explored for non-comparative purposes and merely in the interest of completeness and representativeness.

The following conclusions were drawn from the results of the independent sample *t*-tests:

- There were no significant differences between females and males when comparing their social influence, perceived risk and perceived customer value and their behavioural intention to continue using same-day delivery apps ($p \geq 0.05$) (see Chapter 6, Table 6.31).
- No significant non-conformities between the generational cohort groups (i.e. young and old consumers) were found when comparing their social influence and perceived behavioural intention and their behavioural intention to continue using same-day delivery apps ($p \geq 0.05$) (see Chapter 6, Table 3.32).

- Significant mean differences between the Baby Boomer and Generation X cohort (or the older generation) and the Generation Y and Generation Z cohort (or the younger generation) with regard to perceived risk was evident ($p \leq 0.001$) (see Chapter 6, Table 3.32). It is apparent that Baby Boomers and Generation X-ers seem to be more risk-averse than Generation Y and Generation Z consumers. Cohen's *d* was investigated to establish the effect of the invariance between the generational groups and perceived risk. Despite achieving statistical significance, the actual difference in mean scores was quite small ($d = 0.312$) and thus regarded as unremarkable.

Although no statistically meaningful differences were found in the research study between individuals from different demographic backgrounds, the following conclusions were drawn from the small effects evident in the data: Generation Y and Generation Z, or younger consumers (born between 1990 – 2003), were influenced somewhat more, albeit to a small degree, by perceived risk when deciding whether to continue using same-day delivery apps than Baby Boomers and Generation X-ers, or older consumers (born between 1950 – 1989). It was inferred that, because individuals from Generation Y and Genration Z generally tend to shop online more frequently and broadly than Baby Boomers and Generation X-ers, they have more likely experienced online fraud and, as a result, is more sceptical and cautious of adopting new online shopping platforms. On the contrary, it can be inferred that, during the COVID-19 pandemic and need for social distancing, Baby Boomers and Generation X-ers (older consumers) offset the risk of physically having to go to the store, increasing their chances of contracting COVID-19, with the minimal risk associated with purchase products through a reputable same-day delivery app.

The test for group mean differences provided supporting evidence for empirical research objective 7. No statistically noteworthy differences could be found between individuals from different generational cohorts or genders in relation to their intentions to continue using same-day delivery apps.

7.3.3 CONCLUSIONS REGARDING THE PRIMARY OBJECTIVE

The study aimed to examine the factors influencing South African consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model. The achievement of this primary objective was systematically addressed through a series of secondary objectives, as discussed in section 7.3.1 and 7.3.2 respectively.

In addressing the literature research objectives, the study explored international and South African contexts, evaluating mobile apps and same-day delivery app usage within the retailing industry. The assessment of the UTAUT2 Model's methodological rigour provided a foundation for the conceptual model, identifying validated constructs influencing consumers' behavioural intentions towards new technology. The conceptualisation of constructs and exploration of theoretical interrelationships, including moderating effects such as generational cohort and gender, laid the groundwork for the development of a comprehensive conceptual model.

Proceeding to the empirical research objectives, the study investigated consumers' use of same-day delivery apps in the South African market. The findings confirmed the widespread adoption of online technologies during the COVID-19 pandemic, with food delivery apps established in the market, while grocery-related same-day delivery platforms exhibited lower penetration, potentially due to factors such as limited knowledge and reach. The examination of the research instrument's suitability revealed positive responses from participants regarding factors influencing behavioural intention to continue using same-day delivery apps. The subsequent assessment of the measurement model's validity, however, presented challenges, necessitating modifications. The revised model, emphasising social influence, perceived risk, and a new construct termed perceived customer value, demonstrated satisfactory goodness-of-fit outcomes and validated convergent and discriminant validity. Correlation analyses identified significant associations between independent variables (social influence, perceived risk, and perceived customer value) and behavioural intention. Social influence and perceived risk, however, did not emerge as statistically significant predictors in the structural equation modelling, whereas perceived customer value played a central role, explaining a substantial percentage of the variance in behavioural intention. The examination of moderation effects revealed that demographic factors, namely generational cohort and gender, only marginally impacted the relationship between perceived customer value and behavioural intention. Finally, the study's exploration of significant differences between individuals from different demographic backgrounds found no statistically noteworthy distinctions in their intentions to continue using same-day delivery apps.

In conclusion, the research successfully achieved its primary objective by examining the factors that influence consumers' behavioural intention to continue using same-day delivery apps, and thereby developing and empirically testing a consolidated technology acceptance model tailored to the South African context. The study contributes valuable insights into the factors shaping consumers' behavioural intentions regarding same-day delivery apps, emphasising the significance of perceived customer value and providing a better understanding of moderating

effects influenced by demographic factors. The primary objective of the research study was therefore achieved.

The following section addresses the limitations of the research study.

7.4 LIMITATIONS

The research study had certain limitations that can be addressed in future research undertakings. Acknowledging limitations in a research study is vital as it fosters transparency, intellectual honesty, and a realistic interpretation of findings. Identifying and openly discussing limitations demonstrate the researcher's awareness of potential constraints, ensuring the audience gains an understanding of the study's scope and potential implications. This acknowledgment not only enhances the credibility of the research but also guides future investigations by highlighting areas for improvement or refinement. It promotes a culture of continuous learning within the scholarly community, encouraging researchers to critically assess their work and refine methodologies for more robust and reliable outcomes. These limitations are elaborated on below.

Firstly, sources consulted on major subject databases, such as ScienceDirect, EBSCOHost, ProQuest, Emerald and Google Scholar, about the mobile app market and specifically same-day delivery apps were limited and mostly of international origin. Limited South African research or research specific to same-day delivery apps or the on-demand mobile service market could be found (refer to Annexure A). Conceptualisation and the conceptual model were therefore built mainly on the theories and findings of international origin. Although comparative conclusions with international countries can be drawn, the theory might not be relevant in a South African context.

Secondly, data for the preliminary and final research instrument were collected in 2021. During this period South Africa was faced with economic turmoil (The Economist, 2021; The Presidency, 2021), which likely impacted the results of the research study. First of all, the civil unrest which took place in KwaZulu-Natal and Gauteng after the imprisonment of former President Jacob Zuma for contempt of court could have encouraged individuals residing in these regions to rather purchase through online platforms to avoid physically having to enter areas where violent uprisings took place (The Economist, 2021). Participants could have placed increased importance on certain factors, such as perceived customer value, which might not have been the case had riots not been in the equation. Furthermore, South Africa was faced with the aftermath of the worldwide COVID-19 pandemic generally brought about by national lockdown restrictions that were enforced by the Minister in terms of the State of Disaster Management Act: COVID-19 (Republic of South Africa,

2020: 4). The country was under adjusted alert level 3 from 26 July 2021 to 12 September 2021, after which the restrictions were eased to alert level 2. Consequently, these lockdown restrictions conceivably impacted the results of the research study. The following lockdown restrictions, pertinent to the research study, were in effect at the time of data collection (Republic of South Africa, 2021):

- Every person was confined to their place of residence from 22:00 until 04:00 daily.
- Restaurants, bars, shebeens and taverns were to close at 21:00 daily, both indoor and outdoor establishments.
- The wearing of a face mask was mandatory for every person when in a public place and social distancing of 1.5 to 2 m between persons was always required.
- Supermarkets, shops, grocery stores, retail stores, wholesale produce markets, pharmacies etc. were required to determine their floor space and thus limit the number of customers and employees that were allowed inside the premises at any time to maintain adequate social distancing of at least 1.5 m between persons.
- The sale of liquor for offsite consumption was only permitted from 10:00 until 18:00 from Mondays to Thursdays, excluding Fridays, Saturdays, Sundays and public holidays.
- The sale of liquor by a licensed premises for on-site consumption was permitted until 20:00.

The lockdown regulations listed above could have had certain implications, which likely impacted the results of the research study. Primarily, the nationwide curfew and restriction of not being able to sit down at a restaurant for a meal during alert level 1 could have led to an increase in take-away orders or home deliveries. Consumers were limited in terms of obtaining food and therefore resorted to other options to obtain takeaways or groceries. The mandatory wearing of a face mask and social distancing requirements furthermore led to individuals avoiding stores and turning towards online platforms to purchase products and the need for home deliveries. These lockdown restrictions inevitably affected the results of the study. Participants placed more value on certain factors, such as the perceived benefits and risks (risk of being safe from the virus) above the importance of other factors as intended by Venkatesh et al. (2012) in the development of the UTAUT2 Model. Conceivably these could be the reasons for the lack of discriminant validity that was evident among the constructs of the original measurement model. Participants might have waived the importance of certain factors (such as in the case of the research study) to compromise for the lockdown restrictions enforced by the government. Where, under normal circumstances, a factor might have been important, individuals might have considered their own health and safety as more important than the specific factor in question.

Thirdly, the demographic composition of the respondents who participated in the research study was unequal, thereby restricting the generalisability of the results. 54% of the 485 respondents who participated in the study were born between 1990 and 2000, also classified as Generation Y-ers. The findings of the research study are therefore limited to this cohort in South Africa. In addition, the sample consisted mostly of female respondents (69.5%). Although females are generally the persons in a household who purchase groceries and food, a more equal distribution of genders might have yielded different results as males and females place importance on different factors influencing their decisions and intentions. By implication, the findings of the research study are limited to females. Furthermore, the sample was drawn from only three of the nine South African provinces, namely Gauteng, KwaZulu-Natal and the Western Cape, with most of the sample being from Gauteng (60%) and KwaZulu-Natal (21.9%). The findings of the research study may thus not be representative of the broader South African population.

Fourthly, the research study was only quantitative in nature. Even though the sample size (n = 485) was considered substantial, a qualitative or mixed method investigation may have provided greater understanding and insight for same-day delivery app owners and developers or retailers in general. A qualitative or mixed method approach could have shed light on other potential latent factors that could influence consumers' behavioural intention towards same-day delivery apps. The literature offers many latent variables that potentially influence behavioural intention in the adoption of technology. Qualitative research could therefore have produced factors more pertinent to the context and sample in question.

In the fifth place, the research study employed a cross-sectional design, which provides valuable insights at a specific point in time. However, it is worth considering that a longitudinal study could offer additional insights by examining changes in consumers' behavioural intention and actual use behaviour over a period of time, such as during the worldwide pandemic and post-pandemic.

Sixth, self-reported assessments were used as the study's instrument. Although self-reporting measures are widely used to analyse individual perceptions, attitudes, and behaviour, they have some disadvantages. The results of self-reporting measures may be skewed because participants may lack the ability to reflect or recollect specific information, resulting in inaccurate responses to questions despite their best efforts to provide true and honest answers (Kirsten, 2019: 642). Furthermore, self-report measures are susceptible to common method bias (CMB), which is increased by gathering data on both independent and dependent variables from the same sample (Podsakoff, MacKenzie, Lee & Podsakoff, 2003). When employing a single method for data collection, the observed relationship between variables deviates from the true relationship

(Kirsten, 2018:643). As a result, it is concerned with variance that can be linked to the measurement procedure rather than the constructs represented by the measurements (Podsakoff et al., 2003). To reduce this bias, Podsakoff, MacKenzie and Podsakoff (2012) proposed several preliminary precautions with the data collection method and the conceptualisation of the framework. Respondents were assured of the study's anonymity and confidentiality, that there was no correct response, and that they were asked to answer as honestly as possible. To improve construct validity, already verified measurement instruments were used (refer to chapter 5, section 5.2.5). For the questionnaire items, different scales were used. Furthermore, the sequence of each scale items was randomly sorted to minimise associations between them, hence minimising biased response patterns. Furthermore, complicated interactions between the dependent and independent variables were discovered (i.e. moderating effects guided by applicable theory).

Lastly, individuals who indicated that they did not own a smartphone and did not already use same-day delivery apps were excluded from the research study as the study intended to investigate which factors influenced participants to use same-day delivery apps. Including individuals who did not use same-day delivery apps may have produced different and comparative results to those individuals who were already using these types of apps and might have been predisposed to use same-day delivery apps.

The following section presents recommendations for future research projects and industry recommendations taken from the results discussed in Chapter 6, the conclusions observed in Chapter 7 and the limitations presented above.

7.5 RECOMMENDATIONS

Based on the results that were discussed in Chapter 6, the conclusions that were drawn from the results and the limitations associated with the research study, various recommendations can be offered to retailers, food outlets, app owners and developers, as well as for future research studies. The recommendations for industry and future researchers are discussed below.

7.5.1 RECOMMENDATIONS FOR INDUSTRY

Based the conclusions drawn from the results, the following recommendations can be offered to same-day delivery app owners and app developers in South Africa.

Recommendation 1: Establish an online and/or mobile presence.

The results revealed that consumers frequently use various online shopping platforms and technologies available in the South African market (see Chapter 6, section 6.2.2), and therefore it was presumed that an online presence is substantial in the South African retail and restaurant industry. It is recommended that retailers and food outlets adapt their business model to include an online shopping presence, whether it be on an online platform or a mobile app.

Furthermore, the results have shown that same-day delivery apps have value in the South African market (see Chapter 6, section 6.2.2). The COVID-19 pandemic, civil unrest, consumers' busy lifestyles and the convenience offered by instant home deliveries have driven consumers' need for a same-day delivery option when shopping online. In the past few years, customers have increasingly become aware of the availability and convenience of home deliveries and on-demand services and tend to seek out those services that offer convenience and swiftness (Ahuja, Chandra, Lord & Peens, 2021; Nunez, 2021; Wood, 2020). Customers are increasingly demanding on-demand services from a variety of retailers, including restaurants/fast-food outlets, grocery stores, pharmacies and fashion retailers. It is therefore recommended that retailers and food outlets explore the possibility of implementing on-demand home delivery services in their business model to reach a wider South African audience and capture the market demanding same-day delivery opportunities.

Recommendation 2: Create awareness.

The results have shown that restaurant same-day delivery apps, such as Debonairs Pizza, Mr D Food and Uber Eats, are most often used by consumers compared to grocery-related same-day delivery apps, such as Checkers Sixty60, Woolies Dash or Pick n Pay ASAP! (see Chapter 6, section 6.2.2). The low penetration rate could have been because of (1) the early stages of grocery-related same-day delivery apps in the South African market as these apps were first launched in 2020 and data were collected in 2021, (2) consumers' limited knowledge of grocery-related same-day delivery apps and/or (3) the limited reach of grocery-related same-day delivery apps in the market as only certain participating retailers had implemented these apps at the time of data collection. Although the reach has extended into a wider market, it is recommended that retailers implement various marketing strategies across different platforms to increase awareness and reach.

Retailers and/or app developers could consider implementing the following strategies to attract customers to same-day delivery apps:

(a) Implement special offers that are unique or solely linked to the app, for example offering app-only promotions. Customers would need to utilise the app to benefit from the special offering or discount.
(b) Implement a loyalty programme on the app, or incorporate existing loyalty programmes in which customers can get rewarded for utilising the app.

(c) Offer incentives, discounts or rewards for sharing, liking and recommending the app on social media platforms.

(d) Similarly, offer discounts, rewards or competitions if customers review the app itself, or the products or services are bought via the same-day delivery app.

Recommendation 3: Emphasise the augmented and auxiliary services available on same-day delivery apps.

Retailers and food outlets should emphasise and leverage the augmented and auxiliary services offered by same-day delivery apps, as the results reveal that most consumers use same-day delivery apps because of their convenience and the safety offered against the COVID-19 pandemic and civil unrest which occurred in South Africa at the time of data collection for the study (refer to Chapter 6, section 6.2.2.3). Although the COVID-19 pandemic and civil unrest could have impacted the results of the research study, marketing strategists should nevertheless highlight additional services and benefits offered by same-day delivery apps, such as app-only specials or coupons, the app's ability to compare products and prices, the benefits of leaving or reading reviews and/or the ability to check product availability and store information.

Recommendation 4: Focus on the aspects that are important to consumers.

In view of the results and conclusions about the average mean scores of the statements related to the initial 11 constructs, the following recommendations are offered (see Chapter 6, section 6.3.1):

(a) On average, consumers surveyed agreed with the statements that same-day delivery apps allowed them to save time, which enabled them to do something else and, as a result, increase their productivity. App developers should therefore ensure that the entire shopping

experience and process is quick, it is simple to navigate, has an easy search function and effortless checkout and payment options, and results in quick and seamless delivery of products.

(b) On average, consumers surveyed believed that same-day delivery apps were beneficial to them, offered useful functions and allowed them to accomplish their shopping goals quicker. App developers must create a user-friendly interface (Kristijan, 2022) and design a same-day delivery app by considering and leveraging the capabilities offered by smartphones. Some examples are as follows:

- The user can use the smartphone's camera to scan the barcode of grocery items that they need to replace, which is then instantly added to their shopping cart on the app when scanned.
- The GPS functionality can be utilised to easily locate the closest store and pinpoint the customer's location for effortless checkout and delivery.
- The customer can customise and personalise their profile on the app to receive targeted push notifications.
- The customer can utilise the built-in virtual assistant technology and voice recognition software of the smartphone (e.g. Siri) to navigate the app and easily search for products.
- Multi-device synchronisation can be implemented so that the app can be used across platforms.
- The customer's personal purchase history and data related to frequently bought items can be utilised to recommend products, remind customers to purchase staples and track their shopping habits (e.g. how regularly a customer purchases milk or bread and send reminders).
- It is furthermore advised that app developers consider the screen size of the smartphone. The app experience should be carefully considered when designing the app, allowing for simple browsing and navigation by one hand and one thumb (Van Niekerk, 2020: 304).

(c) New and improved app functionalities should be released that make the app more relevant and valuable to the user, thereby enticing users to continually use the app and encourage others to download it as well (Van Niekerk, 2020: 304). App owners must ensure that new and improved versions of the app, together with the latest capabilities and functionalities, are advertised and clearly communicated to customers.

(d) Design a same-day delivery app that is instinctive, user-friendly, effortless and straightforward to use. Same-day delivery apps should be well thought through and well designed, allowing for easy navigation, simple browsing, effortless checkout and payment, and generally requiring minimal effort, both mentally and physically (Chopdar et al., 2018: 122; Van Niekerk, 2020: 306). App developers could consider implementing 'how to' screens, logical product grouping and categorisation, scalable text, an avatar and a straightforward search option. Additionally, it is recommended that app owners and developers design and align the app's functions and features to resemble similar shopping apps so that the app is more intuitive and easier to use (Van Niekerk, 2020: 207).

(e) It is expected that individuals will use mobile apps if they have already formed habitual behaviours towards shopping via their mobile phones (Alalwan et al., 2016: 134). Consumers surveyed generally agreed with the statements that purchasing through same-day delivery apps had become a habit, automated or second nature to them. As highlighted in the previous point, same-day delivery app developers should consider incorporating design thinking principles from popular and widely-used shopping apps to ensure that same-day delivery apps feels familiar and intuitive to the user (Van Niekerk, 2020: 315). Aligning the design of the same-day delivery app with best practices will guarantee an easy-to-use, instinctual app whose usage will become routine and habitual more quickly (Miladinovic & Xiang, 2016: 54).

(f) Habitual behaviour towards the use of same-day delivery apps can be encouraged and maintained by regularly sending personalised and targeted push notifications and new product announcements to the customer according to the user's personal information and shopping history or data, sending reminders to users based on their purchase history and purchasing data and incorporating a loyalty or rewards programme into the app to incentivise continued usage. Loyalty member benefits could include exclusive access to in-app specials and discounts, tailored discounts based on a user's past purchases, a reward point system and/or a reward tier system where frequent users will receive bigger discounts or rewards the higher they are on the loyalty hierarchy.

(g) The results reveal that consumers, on average, felt that they were knowledgeable, well equipped and had the required resources to use same-day delivery apps successfully, without the help of others. To maintain adequate operating conditions, same-day delivery app owners and developers must design a user-friendly and responsive interface, ensure app stability and reduce app down-time, system failures, errors or technical breakdowns. The app should be able to function efficiently with many customers browsing the app and be

able to handle multiple orders and checkouts simultaneously without technical faults. Same-day delivery app owners should aim for the industry standard of a 99.9% up-time (Intelliwave Technologies, 2019). Should any technical errors or interruptions occur, app owners should promptly communicate the problem to the customer, issue an apology and state how the problem will be corrected to reassure customers (Van Niekerk, 2020: 304). Furthermore, same-day delivery app developers should design a same-day delivery app that is compressed in size to allow for quicker response time (Van Niekerk, 2020: 310). Even though the response speed of shopping apps is largely influenced by the network service provider, app developers need to design a small and compressed app to ensure limited data consumption and thereby ensure quicker response times on the app (Madan & Yadav, 2016: 239). Kristijan (2022) advises that app speed can be optimised by reducing the number of loads on the app (i.e. reducing the number of times a customer must click to achieve a task), reducing the number of images, using pre-built themes and using a simple layout. Hew et al. (2015: 1286) also propose the use of simplified language and icons to streamline the use of the app. Implementing these suggestions will ultimately allow the user to navigate the app's functionalities effortlessly. Customers want a seamless experience and clearly understand what to do with the app.

(h) Same-day delivery app developers should consider the app's compatibility and functionalities across other technologies linked with the user's mobile device, such as a tablet or smartwatch (multi-device synchronisation). Users should be allowed to shop on different devices and receive notifications on the various linked devices. For example, the user can receive a shopping progress update on their phone and through their smartwatch. App developers also need to consider the layout across platforms, for example a tablet's screen size compared to that of a smartphone and smartwatch.

(i) Consumers surveyed agreed, on average, that they used same-day delivery apps because they were fun, enjoyable and interesting to use, and they experienced gratification when using these types of apps. Same-day delivery app owners and developers can ensure continued enjoyment of same-day delivery apps in the following ways:

- Producing not only a well-designed app but also an app that is pleasurable to use by integrating elements to keep customers engaged;
- Creating industry-specific content and related specials, for example advertising braai meat before a rugby match;
- Incorporating competitions or sweepstakes, such as finding a hidden character while browsing the app, earning rewards for shopping online which can be used on the next

order, an online spin-the-wheel competition to qualify for discounts, or automatic entry into a lucky draw competition;

- Including personalised messages or avatars to assist users throughout the shopping experience;
- Including recipes or dinner suggestions on the app along with the grocery items needed that can be added to the shopping cart with one click.

(j) Consumers surveyed typically agreed with the statements that the cost of using same-day delivery apps was reasonable and good value for money. It is suggested that same-day delivery app owners outline the benefits offered by the app, such as stating the cost-effectiveness compared to the current high price of petrol. Most delivery services comprise a service fee and/or a delivery fee. App owners could:

- Provide users with the option of purchasing a month pass at a fixed monthly fee for free deliveries or a free service fee to attract customers and encourage repeat purchases;
- Offer free delivery if orders exceed a certain amount;
- Aim for a zero-rate mobile data usage model for the app, meaning that users will pay to download the app, but not to use the app;
- Create a free shopping window (free delivery and/or free service fee) to increase traffic during quiet times of the day and thereby reduce pressure on the system during peak hours;
- Offer daily deals;
- Monetise apps in different ways, such as selling advertising space.

(k) Although the results suggest that consumers are confident in their own abilities to use same-day delivery apps without the help of others, it is recommended that same-day delivery app developers incorporate a customer support function into the app. Strategies to consider are to:

- Include solutions to frequently asked questions;
- Have 24-hour, 7-days-a-week support service available;
- Provide the contact details of support personnel, and ensure that the details can easily be found by the user;
- Offer a portal to effortlessly lodge problems with current orders or past deliveries, such as missing items, incorrect products delivered, damaged or spoilt products, and allow the customer to select their desired outcome (for instance receiving credit for damaged or missing items);

- Offer a customer complaints, compliments and/or recommendations portal;
- Offer a service chatbot. Chatbots offer automated and personalised assistance to customers at any time and location, often at a lower cost compared to employing a team of customer service representatives (Van Niekerk, 2020: 311).

(l) Generally, customers are satisfied with and have a favourable attitude towards to the use of same-day delivery apps and will likely use these types of apps as opposed to other methods of purchasing products. App owners can leverage on the favourable attitude customers have towards their apps by prompting them to rate and review the app, app experience or products bought on the app. This will ultimately encourage other users to download and use the app as well.

(m) Consumers surveyed, on average, agreed with the statements that same-day delivery apps are an important source of information. It is therefore recommended that app owners include as much information as possible to users, but only the necessary information. Information could include product availability, price, product sizes, store information and contact details.

Recommendation 5: Strive for favourable reviews and recommendations from current app users.

Social influence was one of the key constructs that was retained in the revised measurement model presented in Chapter 6, Figure 6.3. A significant and positive association between social influence and behavioural intention was evident with Pearson's product-moment correlation coefficient (refer to Chapter 6, section 6.6.1). High levels of social influence were associated with high levels of behavioural intention. The SEM analysis, however, rejected the hypothesis that there is a significant relationship between social influence and behavioural intention to continue using same-day delivery apps (H_a1). A negative and statistically insignificant relationship was reported – refer to Chapter 6, section 6.6.2.2.

Although the relationship between social influence and behavioural intention was statistically insignificant in the research study, generating favourable perceptions among users will increase the likelihood of them recommending the app and providing favourable reviews. The following actionable recommendations are offered to same-day delivery app owners:

(a) As previously mentioned (see recommendations 4d and 4e), app developers should produce a same-day delivery app that is well designed, intuitive, functional and effortless to use, in order to give users a favourable shopping experience. Overall app experience will influence

consumers' general perception of the app and influence the possibility of sharing positive reviews and commendations with others.

(b) Encourage customer feedback by offering incentives, such as being entered into a lucky draw competition. It is important to note that customers can be incentivised to provide reviews in-app, which can only be viewed by other users. Many app stores, such as Apple's App Store, does not allow app owners to incentivise users to review the app on the App Store itself.

(c) Make it easy and convenient for users to rate and review the app, products and/or service on the app and consider the most appropriate time to ask users to rate the shopping app, for instance after the products have been delivered.

(d) Leverage positive reviews or 'best in practice' rewards by communicating these appraisals in advertising material.

(e) Offer users the option to easily share the app with other people. App owners can consider offering a reward to those users who share the app. For example, a user receives a unique URL link or code that they can send to others. If an individual signs up using that unique URL link or code, the sharer and new user will receive a discount voucher, reward or other incentives for the referral and sign-up.

(f) Be responsive to both positive and negative reviews. Respond to unfavourable or negative reviews by apologising to the customer and stating a solution. Responding to unfavourable reviews will show potential users that the app owner is eloquent and passionate about the opinions and experiences of all users, and provides quick solutions to problems.

(g) Allow users to rate and review the same-day delivery app and the products bought on the app. Allowing customer reviews will show credibility to potential users. Customer reviews are a more reliable source than other sources of information and research has shown that customer reviews have a significant influence over consumers' purchasing decisions (Van Niekerk, 2020: 308-309).

(h) Incorporate social interactions into the same-day delivery app. M-commerce customers want shopping apps to have the option to share content on social media (Kravtsov, 2018). Integrating social networks enriches the user's experience and satisfies a natural desire to connect with others, keeping them engaged within the app, and adds a personal element to their shopping experience. Sharing experiences with others naturally increases traffic to the app and can lead to higher sales (Kravtsov, 2018).

Recommendation 6: Mitigate risk factors associated with mobile shopping apps and create a trustworthy and credible same-day delivery app.

Perceived risk was the second key construct that prevailed in the revised measurement model presented in Chapter 6, Figure 6.3. A significant and very low negative association between perceived risk and behavioural intention was evident with Pearson's product-moment correlation coefficient (refer to Chapter 6, section 6.6.1). High levels of perceived risk were consequently associated with lower intentions to use same-day delivery apps. Therefore, if the risks associated with using same-day delivery apps pose too many uncertainties, individuals will have less intention to continue using same-day delivery apps. The SEM analysis, however, rejected the hypothesis of a significant and negative relationship between perceived risk and behavioural intention to continue using same-day delivery apps (H_a2). A negative but statistically insignificant relationship was reported – refer to Chapter 6, section 6.6.2.2.

The results show that there is an inverse relationship between perceived risk and behavioural intention, albeit a statistically insignificant one. Recommendations are nevertheless offered to same-day delivery app owners and developers to ensure that risk factors associated with mobile shopping apps do not negatively influence users' inclination to use same-day delivery apps:

(a) Only ask users for the necessary information to complete an order and transaction (Kristijan, 2022). Personal information relevant to same-day delivery apps are the customer's name, contact details and physical location.

(b) When subscribing to the same-day delivery app, offer users a guarantee that the information they provide will not be given to third parties. The sharing of personal information is governed by the Protection of Personal Information (POPI) Act and should be enforced by company policies. Furthermore, give users the option to receive or opt out of newsletters, advertisements or special offerings from the retailer.

(c) Give app users the option of whether they want to save their payment information and/or delivery location on their personal profile for easy checkout. In this way, if a user feels it is too risky to save payment information and/or their physical address on the app, they are not obligated to do so and can enter the details every time they shop.

(d) Give customers various reliable and credible payment options to choose from. Payment options include paying by cheque or credit card, instant EFT by PayFast which requires the user to access their internet banking profile to complete the payment, Mobicred which offers customers credit that can be used to pay online through PayFast, MoreTyme which allows

customers to buy now and pay later, or SnapScan and Zapper which use QR codes to scan and pay for online orders.

(e) Create partnerships with affiliations such as eBucks or Discovery Miles and allow users to not only generate rewards with these partners, but also allow customers to use their eBucks and Discovery Miles to purchase products on the same-day delivery app.

(f) Offer app users the option to pay in cash once the items are delivered. In this way, customers avoid the risk of giving out payment information or losing money for purchases that are not delivered, especially if the retailer or food outlet is not yet well established in the market.

(g) Establish an easy and convenient portal for customers to report complications with ongoing or previous orders, with actionable solutions to problems. Therefore, app owners must establish an easy and convenient refund policy. To avoid an unnecessary monetary loss to the app owner, the app owner needs to have quality control measures in place before an order is completed and sent out for delivery.

(h) Establish a truthful and transparent complaint-handling procedure and policy (Van Niekerk, 2020: 319). It is important for customer service agents to be empowered to acknowledge and rectify any mistakes that occur. Keeping the customer informed about the progress made in resolving their complaint is crucial for building trust and maintaining a positive customer relationship.

(i) Leverage online reviews and recommendations of other users to build trust and include trust elements into marketing campaigns to instil confidence in customers (Van Niekerk, 2020: 320). Along with this, same-day delivery app owners should apply for security accreditations and surface these security accreditations on the app. If a same-day delivery app accepts major credit cards, it is essential for the app owners to apply for a Secure Socket Layer (SSL) certificate. This certificate is mandatory and ensures the secure transmission of sensitive data, providing customers with a safe and trustworthy shopping experience.

(j) Constantly communicate to customers about the process of the order, inform them should there be a delay in the shopping process and provide an estimated time of arrival.

(k) M-commerce users are faced with a range of security threats, including phishing, data errors, unprotected online services, credit card fraud and hacking. User credentials and personal information are more prone to leakage on mobile apps; mobile app owners must therefore take precautions to minimise fraudulent transactions. To defend against these threats, same-day delivery app owners must ensure that they update the platform's operating system regularly, deploy PCI-DSS (Payment Card Industry Data Security Standard) scans and updates and server content on HTTP and use SSL.

(l) Implement multifactor authentication, which is an extra layer of protection to a user's profile or account in addition to the login and password. Multifactor authentication could comprise a one-time password (OTP) or PIN e-mailed or texted to the user's device or using the smartphone's biometric capabilities for authentication.

(m) Create a credible-looking app and image and portray the image throughout the online purchase and delivery process. Delivery partners should look professional, be friendly and, where possible, drive recognisable and branded vehicles and wear identifiable clothing of the specific retailer to avoid the potential risk faced by individuals opening the gate to strangers (Saras, 2020).

It is advised that the developed conceptual model as presented in the study be adopted as the preferred instrument for establishing consumers' behavioural intention concerning the continuous use of same-day delivery apps. The conceptual model offers industry practitioners and fellow researchers with a comprehensive and validated framework for evaluating and enhancing consumer engagement with same-day delivery apps.

Recommendation 7: Generate substantial value for customers.

Perceived customer value emerged as a latent variable in the construction of the revised measurement model (see Chapter 6, section 6.4.2). Pearson's product-moment correlation coefficient has shown a significant and high positive correlation between perceived customer value and behavioural intention. As a result, high levels of perceived customer value were associated with high levels of behavioural intention (see Chapter 6, section 6.6.1).

The SEM analysis, discussed in Chapter 6, section 6.6.2, confirmed the significant relationship between perceived customer value and consumers' behavioural intention to continue using same-day delivery apps – accepting the alternative hypothesis (H_a3). Perceived customer value was shown to exert the most influence on consumers' behavioural intention (85.7%), and as a result, was the most important factor derived from the research study. It is therefore imperative for same-day delivery app owners and developers to create value for customers. Customers weigh up the benefits derived from using a product/service against the sacrifices they must make to use it. The results reveal that consumers place greater value on same-day delivery apps if the apps provide utility through productivity, ease of use, fun and excitement, and cost-effectiveness.

Taking the recommendations made above into consideration will allow app owners to offer a same-day delivery app that provides value to the customer, thereby compensating for the losses incurred

by the user to receive the benefit offered by same-day delivery apps. Recommendations 4(a), 4(b), 4(e), 4(f), 4(h), 4(i), 4(j), 4(k), 4(l), 4(m) and 5(h) have specific reference to upholding adequate value to customers.

Recommendation 8: Consider the diversity and needs of the consumer market.

In view of the results about the differences, albeit small, between individuals from various generational cohorts (age groups) and genders in the factors that influence their behavioural intention to continue using same-day delivery apps, the following recommendations can be made for same-day delivery app owners and developers:

(a) Perceived customer value is slightly more important to female consumers than male consumers (refer to Chapter 6, section 6.6.3.1). Same-day delivery app owners must therefore leverage the loyalty of existing female consumers and find ways to attract male consumers by offering them increased benefits which outweigh the sacrifice they must make to use the app.

(b) Perceived customer value is slightly more important to Baby Boomers and Generation X-ers (1950 – 1989) than Generation Y-ers and Generation Z (1990 – 2003) (refer to Chapter 6, section 6.6.3.2). As a result, same-day delivery app owners should leverage the loyalty of the older generation (Baby Boomers and Generation X), offer incentives for the older generation to recommend, review and rate the app and find ways to attract the younger generation (Generation Y and Generation Z). Same-day delivery app owners should provide benefits to the younger generation which outweigh the sacrifices associated with using these types of apps.

(c) The Generation Y and Generation Z cohorts (1990 – 2003) is furthermore influenced more by perceived risks in continue using same-day delivery apps than the Baby Boomer and Generation X cohorts (1950 – 1989), albeit to a small degree (see Chapter 6, section 6.6.4.2). It can be inferred that younger consumers (Generation Y and Generation Z) are influenced more, albeit to a small degree, by perceived risk when deciding whether to continue using same-day delivery apps than older consumers (Baby Boomers and Generation X-ers). Recommendations made above (see recommendation 6) to mitigate the risks associated with same-day delivery apps could be implemented.

The next section highlights recommendations specifically for future research projects, based on the conclusions drawn from the results of the research study and the limitations presented in section 7.4 above.

7.5.2 RECOMMENDATIONS FOR FUTURE RESEARCH

Based on the conclusions and limitations, recommendations for future research in the field of marketing and retail management are highlighted below.

Firstly, since the violent riots as well as the lockdown restrictions enforced as an aftermath of the worldwide COVID-19 pandemic likely influenced the results of the research study, it is recommended that the study be conducted post-pandemic and post-uprisings. It is suggested that the proposed conceptual model presented in Chapter 1 (section 1.6.1) and Chapter 4 (section 4.3), with the additions of the exogenous mechanisms, be investigated post-pandemic and post-uprising to investigate whether the same revised measurement model emerges from the data (as discussed in Chapter 6, section 6.4.2 and section 6.6.2). It is furthermore proposed that a comparative study be conducted, and the results be compared to the outcomes of this research study to determine whether the COVID-19 lockdown restrictions and riots influenced consumers' perception of which factors are important when deciding whether to use same-day delivery apps in a South African context.

Secondly, it is recommended that future researchers investigate consumers' behavioural intention to continue using same-day delivery apps by applying the UTAUT2 Model in its purest form and as intended by Venkatesh et al. (2012), without the inclusion of exogenous mechanisms that could affect the outcomes of the original UTAUT2 constructs. By contrast, future researchers could investigate other exogenous mechanisms that might influence consumers' behavioural intention to continue using same-day delivery apps. A mixed method approach will provide greater insight into the potential factors relevant in a South African context, as many latent constructs are presented in the literature which could be explored.

Thirdly, the research study only investigated consumers' behavioural intention and omitted 'use behaviour' from the conceptual model, as intended by the UTAUT2 Model. Although the literature suggests that an individual's intention to perform a specific behaviour is the best predictor of whether the individual will perform that behaviour (Ajzen, 1991), measuring actual technology use compared to mere intent could produce different outcomes. Additionally, future researchers might

extend the proposed conceptual model by investigating consumers' continued usage to better understand brand loyalty and return behaviour.

Following on the previous recommendation, researchers can address the limitation of the UTAUT2 Model as suggested in the literature by exploring the 'intention-behaviour gap' (Sheeran & Webb, 2016: 506). Moghavvemi et al. (2013: 247) claim that behavioural intention has a weak predictive and explanatory ability to deal with ambiguity and unexpected events that may occur between the time the intention was formed and the given behaviour was performed. To address the limitation of the UTAUT2 Model, researchers propose including *precipitating occasions or events* as a moderator to measure the impact of external factors on the relationship between behavioural intention and actual use (Moghavvemi et al., 2013: 245; Waehama et al., 2014). The moderator, precipitating events, represents certain exogenous mechanisms that can serve to facilitate or precipitate the realisation of intention into behaviour (Moghavvemi et al., 2013: 249).

The research results presented in the study refer the development of a new latent variable influencing South African consumers' behavioural intention to continue using same-day delivery apps. Various items, according to the CFA results, clustered under the construct labelled 'perceived customer value'. As a fifth recommendation, it is suggested that the newly emerged latent variable, namely perceived customer value, be explored in more depth and as a multidimensional variable. A multidimensional conceptualisation of perceived customer value is required to adequately capture the presence of both cognitive (functional and economic) and affective (emotional, social and epistemic) factors because customers decide to purchase a product after considering multiple consumption values simultaneously (Jansri, 2018: 1; Koller, Floh & Zaunder, 2011: 1157). A multidimensional approach could not be implemented in the study as factor analysis could not be performed because of insufficient items per sub-dimension. Multidisciplinary research has empirically supported the notion that perceived value is multidimensional and can be measured by a variety of instruments (Widhyana, 2019: 9). Although the literature cites many predictors that capture customer value, several of the sub-dimensions can be categorised into four overarching dimensions which were pertinent to the findings of the research study. In the context of this research study, it is proposed that perceived values be viewed in terms of (1) functional value – performance, ease of use and specific outcomes, (2) economic value – monetary and value for money, (3) emotional value – affective, enjoyment, pleasure and passion and (4) epistemic value – novelty, open-mindedness and curiosity, derived from using same-day delivery apps. Future researchers may also consider other sub-dimensions of perceived value depending on the context of the study, for instance conditional value, tangible and intangible values, utilitarian value and service value, to name but a few (see Chang & Dibb,

2012; Groth, 1995; Jansri, 2018; Jelčić & Mabić, 2020; Koller et al., 2011; Sheth, Newman & Gross, 1991; Sweeney, Soutar & Johnson, 1999; Widhyana, 2018).

Figure 7.2 illustrates a proposed conceptual model incorporating the sub-dimensions of perceived customer value that could be investigated in future research studies, or different contexts.

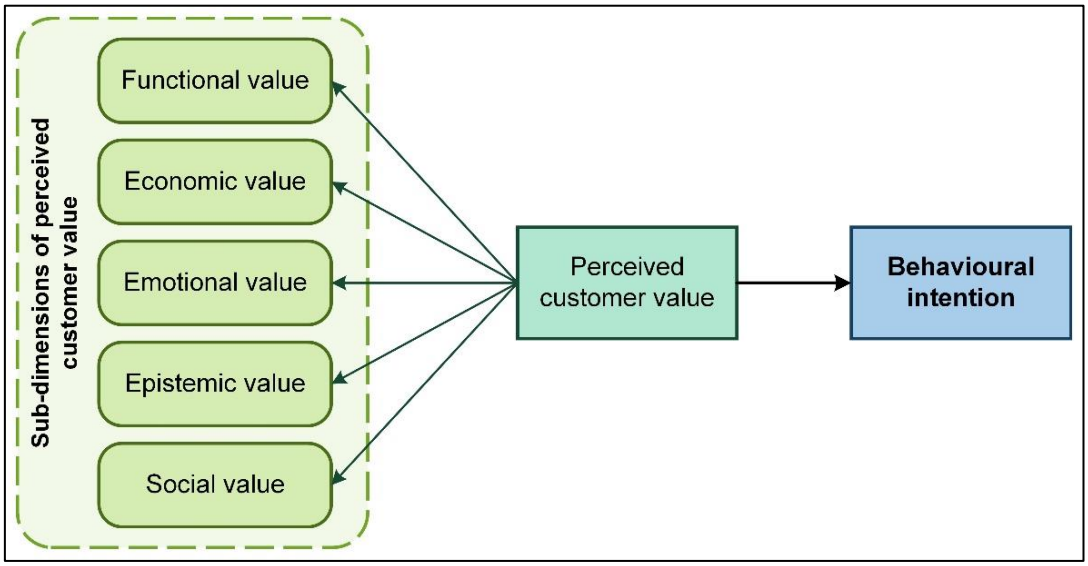

Figure 7.2: Recommended sub-dimensions of perceived customer value for future research projects
Source: Author's own compilation

The sixth recommendation is that future rese archers could further investigate perceived risk and consumers' concerns for safety in more detail. Perceived risk factors can be explored as a first-order construct as examined by Alaimo et al. (2020), Kaushik et al. (2020) and Marriott and Williams (2018), or as a second-order construct as implemented by Fortes and Rita (2016), Marriott and Williams (2018), Thusi and Maduku (2019) and Van Niekerk (2020). Second-order constructs that were explored in prior research include privacy and security, financial risk, product performance risk, device risk and psychological risk. The literature generally describes four types of perceived risk that are of importance in online and mobile shopping, namely product performance risk, privacy risk, financial risk and time or convenience risk (Dai, Forsythe & Kwon, 2014: 15). Trust, which is closely linked with perceived risk and security, could also be included in future research endeavours.

A limitation of the current research study was the cross-sectional nature of the study. The seventh recommendation for future researchers is to conduct a longitudinal study, which could provide additional insights for researchers and industry as it would evaluate the changes in consumers'

behaviour over a period of time, as consumers become more acquainted with the specific technology being researched.

Although self-reported assessments provide valuable insights, their vulnerability to CMB necessitates rigorous testing in future research. To ensure robust and generalisable results, future research should explicitly test for CMB by employing established methods such as Herman's single-factor test, common latent or market variable techniques. By proactively incorporating these CMB testing methods, future research can navigate the potential pitfalls of self-reported measures and draw more accurate, confident conclusions about the phenomena under investigation. This will considerably improve the validity and dependability of research findings, resulting in a more solid foundation for knowledge and future advances in the subject.

Although the research study presented several limitations, it makes a substantial contribution to knowledge by offering valuable insights into adoption and acceptance behaviour research at a theoretical, empirical and practical level. In the next section the research study is evaluated by addressing the contribution it makes to knowledge.

7.6 CONTRIBUTIONS OF THE RESEARCH STUDY

The primary objective of the research study was to examine the factors influencing consumers' behavioural intention to continue using same-day delivery apps, thereby guiding the development and testing of a conceptual model. The findings derived from the research study provided empirical evidence supporting the correlation between three key variables and consumers' behavioural intention to continue using same-day delivery apps, namely social influence, perceived risk and perceived customer value. The empirical analysis, however, resulted in only one hypothesis being accepted (H_a3) –*There is a significant relationship between perceived customer value and consumers' behavioural intention to continue using same-day delivery apps.* Refer to section 6.7 (Chapter 6) for a detailed description of the accepted and rejected hypotheses.

The research study has contributed to three levels of the field of marketing and retail management, namely theoretical, empirical, as well as practical and strategic levels.

7.6.1 CONTRIBUTION AT A THEORETICAL LEVEL

The research study significantly contributed to theoretical and academic advancements by adapting Venkatesh et al.'s UTAUT2 Model (2012) to a different context, specifically the marketing

and retailing industry in South Africa. This adaption involved applying the main effects of the UTAUT2 Model to new user groups within a distinct cultural setting, addressing a notable gap in the literature related to the acceptance of same-day delivery apps in emerging African economies. The UTAUT2 Model was extended by introducing four exogenous mechanisms (perceived risk, lifestyle compatibility, perceived self-efficacy and attitude towards use) to explore their relevance in influencing consumers' behavioural intention.

Furthermore, the inclusion of moderating effects from two demographic variables, namely generational cohort (age) and gender, aimed to examine potential differences in acceptance and adoption behaviour across diverse segments of South Africa's population. The research uniquely conceptualised and defined 11 independent constructs from a marketing perspective, particularly tailored to mobile shopping apps and/or same-day delivery apps within the South African context.

The study's examination of generational cohorts in South Africa not only contributes to the understanding of acceptance behaviour, but also sheds light on the historic events and profound political and societal transformation that demarcated each generational cohort in South Africa, a concept lacking consensus in South African literature. By systematically integrating prevailing literature and conceptualising key constructs within a South African mobile app context, the research developed a robust conceptual model with 11 theoretically derived constructs influencing consumers' behavioural intention to continue using same-day delivery apps (see Chapter 4, Figure 4.1).

Addressing limitations of the UTAUT2 Model highlighted in the literature, the study incorporated perceived self-efficacy and attitude towards use as additional mechanisms, further enriching the theoretical framework. In essence, the research study not only advanced theoretical understanding by adapting and extending an established model but also provided valuable insights into the unique factors influencing consumers' behaviour in the specific context of South Africa's dynamic and evolving market.

The next section addresses the contribution the research study makes at an empirical level.

7.6.2 CONTRIBUTION AT AN EMPIRICAL LEVEL

The research study has significantly contributed to the understanding of consumers' behavioural intention regarding the continued use of same-day delivery apps among a sample of South African

consumers. By constructing and empirically testing a valid and reliable model, the research study has filled a gap in the literature.

One key finding is that the UTAUT2 Model could not be applied to the context of this South African study. Unlike prior research, this study revealed that of the seven original UTAUT2 Model constructs, only social influence influenced behavioural intention, rendering the UTAUT2 Model irrelevant in this context. This finding is in line with Van Niekerk's study (2020: 335) exploring the factors that influence the adoption of m-commerce apps for purchasing athletic fashion apparel in South Africa by extending the UTAUT2 Model. That study found that only performance expectancy and habit influenced behavioural intention, also rendering the UTAUT2 Model irrelevant in the South African context.

The addition of perceived risk as an exogenous mechanism in the development of the conceptual model has proven to be essential in the South African context. Perceived risk was the only exogenous construct included in the conceptual model that remained relevant in the context of the research study and among the sampled population. An inverse correlation was observed between perceived risk and behavioural intention, suggesting that if the perceived risk associated with using same-day delivery apps outweighs the benefits received from using these types of apps, consumers will be less inclined to adopt these apps. A statistically insignificant relationship between perceived risk and behavioural intention was, however, observed (H_a2). Various recommendations were made to industry professionals to mitigate the risks associated with using same-day delivery apps.

Additionally, a new latent variable – perceived customer value – emerged from the empirical results and further contributes to academia at an empirical level. The results reveal that behavioural intention was mostly explained by perceived customer value. The newly derived variable offers innovative insights into the aspects of perceived customer value and its effect on the adoption behaviour towards same-day delivery apps in a South African context. Empirical evidence suggests that consumers consider the productivity derived from using the app, the ease of using the same-day delivery app, the fun and excitement, it being a smart way to shop and the cost-effectiveness of the app as the benefits that outweigh the sacrifices users make to continue using same-day delivery apps. The scale items that constituted the perceived customer value construct encapsulated four sub-dimensions of perceived customer value, namely functional value, economic value, emotional value and epistemic value (refer to Figure 7.2). These findings offer an opportunity for future researchers to explore the sub-dimensions of perceived customer value in adoption behaviour research in South Africa more diligently.

An additional contribution of the research study is that no statistically meaningful differences are demonstrated between individuals from different demographic backgrounds (generational cohort and gender) regarding their behavioural intention to continue using same-day delivery apps in a South African context. Only a practical effect was evident between generational cohort and perceived risk, but the effect was small and considered unremarkable. This finding challenges previously held assumptions and highlights the need for more nuanced and individualised approaches to understanding differences among populations. The research study contributes to a growing body of research that seeks to uncover the complex factors that shape human behaviour and outcomes across diverse populations.

At a practical and strategic level, the research provides a uniquely derived, valid and reliable behavioural intention model specific to the South African context. The revised structural model aids researchers and practitioners in understanding factors influencing consumers' intention to continue using same-day delivery apps, informing more effective marketing and service delivery strategies and contributing to the broader literature on consumer behaviour in emerging markets. The research study is considered original because, to date, there is no existing quantitative study offering a model that integrates the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps. A new model emerged from the data, rendering the UTAUT2 Model irrelevant in the context of this South African research study.

This research study therefore contributes significantly to both theoretical understanding and practical applications in the realm of same-day delivery app adoption in South Africa, offering a new model that surpasses existing frameworks and providing valuable insights for academic and industry professionals alike.

Lastly, the following section summarises the contribution the research study makes at a practical and strategic level.

7.6.3 CONTRIBUTION AT A PRACTICAL AND STRATEGIC LEVEL

At a practical level, the research study contributes to industry knowledge by addressing the shortage of research on same-day delivery apps in emerging African economies, particularly South Africa. Research pertaining specifically to the on-demand economy and same-day delivery apps in emerging African economies is scant (refer to Annexure A). The insights gathered from the data and the resultant conclusions shed light on crucial aspects of m-commerce, the on-demand economy and the South African same-day delivery app market. As a result, South African

retailers, restaurants, app owners and app developers gain a deeper understanding of the factors shaping South African consumers' intentions to continue using same-day delivery apps.
The study's practical contributions to the industry are as follows:

- Given the dynamic nature of the mobile app industry and consumers' increasing inclination towards adopting the latest technological innovations, it is imperative for businesses to continually evolve their business models. Incorporating the latest trends and technologies enables businesses to stay competitive and expand their reach to a broader audience.
- The thriving on-demand economy presents opportunities for businesses to a same-day delivery business model. This strategy allows businesses to cater to the growing demand for same-day delivery services in the South African market, thereby expanding their customer base.
- There is a notable association between consumers' social support networks and their intentions to use new mobile app technology. Hence, fostering positive perceptions among users is crucial, as satisfied users are likely to share favourable reviews and recommend same-day delivery apps within their social networks.
- Consumers are hesitant to adopt mobile shopping apps that pose too many uncertainties and the risk of personal and/or monetary loss. Measures mitigating the risk factors posed by same-day delivery apps should be implemented by mobile shopping app owners and developers to assure users that precautions have been taken and policies enforced to safeguard users' personal and payment information.
- Consumers' intention to continually use same-day delivery apps is determined largely by their perception of value derived from using the app compared to the sacrifices they must make. As the most important factor derived from the results of the research study, it is imperative that same-day delivery app owners and developers create value for their customers. Actionable recommendations were made in section 7.5.1, presenting mobile shopping app owners with strategies to increase the value customers receive from using same-day delivery apps.
- Although only small differences between generational cohort and gender were observed in the results of the research study, recommendations were made to attract a diverse demographic profile of users to use same-day delivery apps (refer to section 7.5.1).

To effectively implement the industry recommendations highlighted in section 7.5.1, which epitomise the primary behavioural intention factors identified in the study, professionals operating

in the on-demand realm, as well as those venturing into the same-day delivery app industry, should prioritise the following key strategies:

- **Generate favourable reviews, recommendations and comments**

Several strategies need to be employed to generate favourable perceptions among users, which will increase the likelihood of users recommending same-day delivery apps to others. For example, encourage users satisfied with the same-day delivery app to share their positive experiences by rating the app on relevant platforms, incentivising their feedback through rewards or competitions. Responsiveness to both positive and negative reviews is important for building user trust and demonstrating commitment to improving user experience.

Marketers should further implement an influencer marketing strategy by taking the idea of celebrity endorsement and placing it into a modern-day content-driver marketing campaign. Influencers are not necessarily celebrities and may include a popular photographer, a well-read cybersecurity blogger, a well-renowned chef, or a respected marketing executive. Consider the number of social media followers of the individual or group and their ability to alter the purchasing decisions of others because of their authority, knowledge, position or relationship with their audience (Geyser, 2022). Marketers should carefully consider collaborations between the brand and the influencers before using the individual.

For additional strategies and specific tactics to encourage user-generated content and positive endorsements, refer to section 7.5.1, recommendation 5.

- **Mitigating perceived risk**

To alleviate user concerns about risk and uncertainties associated with same-day delivery apps, durable safety practices and robust security measures should be implemented to safeguard user data and transactions. For instance, security mechanisms, such as Secure Socket Layer (SSL) certificates, should be properly implemented on mobile apps configured for the highest levels of encryption (Thusi, 2018: 146). Reliable and credible payment options should be offered to users, such as paying by cheque or credit card, instant EFT by PayFast, Mobicred, MoreTyme or SnapScan and Zapper. Users can also be given the option to pay in cash when the order is delivered, which reduces the possibility of payment fraud. Furthermore, partnerships with credible affiliations, such as eBucks or Discovery Miles, can allow the user to generate rewards and use the rewards to purchase through the same-day delivery apps, further increasing the integrity of

the app. A multifactor authentication process should also be implemented to protect users' personal information, such as a pin OTP sent to the user's device to authenticate a transaction.

These substantial resolutions in refining the safety measures in same-day delivery apps will enable retailers to attract new customers and reassure current users to continue using same-day delivery apps. Policy makers should lead in protecting customers against security threats, such as data errors, unprotected online services, credit card fraud, hacking and phishing schemes, which put the customers' classified information at risk, by enforcing policies that make provision for retailers to incorporate advanced security systems into their same-day delivery apps. Retailers should establish a truthful and transparent complaints handling policy and procedure, allowing customer service agents the authority to admit to mistakes made and put the necessary measures in place to address the mistakes and/or complaints promptly to build customer trust.

For additional mitigation strategies and detailed approaches to addressing perceived risk factors, refer to section 7.5.1, recommendation 6.

- **Creating perceived customer value**

To enhance the perceived customer value of same-day delivery apps for South African consumers, focus on developing an intuitive app that provides seamless shopping experience, prioritising user-friendly interfaces and streamlined checkout processes. Personalising push notifications and incorporating loyalty programmes can increase user engagement and retention by offering tailored incentives and rewards based on individual preferences and behaviours. Offering valued-added benefits, such as free delivery or daily deals can further incentivise app users, providing tangible benefits that enhance the overall customer experience and perceived value proposition. Establishing rewards policies based on a tier system for loyalty members can enhance customer satisfaction and loyalty by providing exclusive benefits and privileges for repeat users.

For additional value creation strategies and innovative approaches to enhancing perceived customer value, refer to section 7.5.1, recommendation 7.

- **Understanding the digital landscape**

The digital domain has been redefined over the past few years, with many organisations today venturing into the online and mobile domains to leverage the untapped opportunities they hold

(Van Niekerk, 2020: 337). Engaging professional developers and agencies is essential for ensuring quality app development that meets the specific requirements of the retail industry, leveraging their expertise to design and optimise user-friendly interfaces and functionalities. Regular tracking and analysis of metrics are necessary to adapt to the constantly evolving digital landscape, allowing businesses to identify trends, monitor user behaviour, and make data-driven decisions to optimise app performance and user engagement (Van Niekerk, 2020: 337).

Van Niekerk (2020: 338) proposes guidance on navigating the digital domain and leveraging available channels effectively, providing insights into best practices and emerging trends in the rapid evolving digital landscape.

7.7 FINAL CONCLUSION

Chapter 7 began by providing a brief overview of the entire research study, summarising each of the six preceding chapters. Detailed conclusions structured around the secondary literature and empirical research objectives were drawn, all of which together achieve the primary objective of the research study. Thereafter, the limitations of the research study were discussed. Several actionable recommendations and overarching strategies were then highlighted to assist South African same-day delivery app owners, or those wanting to venture into the on-demand delivery market, in adjusting their business model accordingly to secure a competitive advantage and large market share. Furthermore, recommendations for future research projects were made based on the limitations of the research study as well as the conclusions drawn from the results. Finally, the integration of the research was presented, emphasising the extent to which the research study contributes towards academia and the marketing and retailing industry.

The final empirical research objective (objective 8) was therefore achieved in Chapter 7.

The research study delivers a valid and reliable model that facilitates a better understanding of the key factors that influence consumers' behavioural intention to continue using same-day delivery apps in a South African context.

The research study is thus concluded.

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ANNEXURE A: PRIOR RESEARCH RELATED TO THE CONTEXT OF THE STUDY

Author(s)	Country/ region	Area of study/ subject field	Purpose of study and theory adopted
On-demand/same-day delivery service/apps			
Dablanc, Morganti, Arvidsson, Woxenius, Browne & Saidi (2017)	European cities	On-demand 'instant deliveries'	To investigate the potential of digital marketplaces to disrupt transport and mobility services where numerous app-based services have emerged.
Elango, Dowpiset & Chantawaranurak (2019)	Bangkok	On-demand food delivery apps	To investigate the factors impacting on behavioural intention to use on-demand food delivery apps in Bangkok, Thailand. *Theory*: TAM; TPB
Erwanti, Widodo & Nurhayati (2018)	Indonesia	On-demand mobile service (GO-JEK)	To examine factors influencing continuance intention to use GO-JEK mobile app by employing the UTAUT2 and Information System Success Model. *Theory*: UTAUT2
Fatoki (2020)	South Africa	M-commerce grocery shopping [on-demand delivery service apps]	To investigate the intention of university students to use mobile technology (smartphones) for grocery shopping. *Theory*: TAM
Groß (2022)	Germany	On-demand grocery delivery	To enrich existing findings on purchase behaviour by providing an overview of drivers and barriers to adopting ultra-fast grocery delivery for German consumers.
Irawan & Belgiawan (2022)	Indonesia	Same-day delivery services of food and groceries	To investigate e-shopping behaviour change through ride-hailing apps for grocery and food as an alternative way to minimise out-of-home activities during the COVID-19 pandemic.
Iyer (2019)	India	Food ordering through mobile apps	To understand the influence of demographics such as age, gender, income range, educational qualification and marital status on mobile app food ordering.
Musakwa (2021)	South Africa	Mobile delivery apps	To investigate customer experiences using a South African retailer mobile delivery service app. *Theory:* UTAUT2
Seghezzi, Winkenbach & Mangiaracina (2021)	Italy	On-demand food delivery	To review the extant academic literature on on-demand food delivery services, i.e. the delivery of freshly prepared meals from restaurants to customers enabled by online platforms, and to propose directions for future research in this field.
Xi, Cao & Zhen (2020)	China	Same-day delivery online shopping	To investigate the impacts of same-day delivery online shopping on local store shopping.
Yapp, Balakrishna, Yeap & Ganesan (2018)	Malaysia	On-demand services	To explore the factors driving intention to adopt on-demand services, such as Grab, among male and female technology users in Malaysia. *Theory*: UTAUT2; diffusion of innovation theory (DOI)

Author(s)	Country/ region	Area of study/ subject field	Purpose of study and theory adopted
Online food delivery apps			
Alalwan (2020)	Jordan	Mobile food ordering apps	To identify and empirically examine the main factors predicting the e-satisfaction with mobile food ordering apps and customers' intention to reuse such apps in Jordan. *Theory:* UTAUT2
Baek & Kim (2018)	Korea	Delivery apps	To investigate the structural relationship between environmental factors, personal factors, ease of use, usefulness and behavioural intention of delivery applications by applying the extended TAM. *Theory*: TAM
Belanche, Flavián & Pèrez-Rueda (2021)	USA	Food delivery apps	To examine the phenomenon of food delivery services from the mobile app user's perspective and how consumers' lifestyles are changing because of the convenience provided by the apps. *Theory*: TPB
Benhardy & Ronadi (2020)	Indonesia	Food delivery apps	To investigate what factors are considered by the consumer when choosing an online food delivery app and also deciding if consumers prefer to use first-party or third-party food delivery apps.
Choi (2020)	South Korea	Food delivery mobile apps	To examine the relationships between users' familiarity, perceived ease of use, perceived usefulness, satisfaction and intention to reuse in the context of food delivery mobile apps. *Theory*: Extended TAM
Chotigo & Kadono (2021)	Thailand	Food delivery apps	To examine and compare the crucial factors encouraging Thai customers to use food delivery apps before and during the COVID-19 pandemic on the basis of the modified conceptual paradigm of UTAUT2. *Theory*: UTAUT2
Cho, Bonn & Li (2018)	Korea	Food delivery apps	To explore five salient quality attributes representing convenience, design, trustworthiness, price and various food choices associated with food delivery apps in consideration of their impacts upon user-perceived value, attitudes and intention to continuously use.
Flores & Castaño (2020)	Philippines	Food delivery apps	To identify the influence of food delivery apps on consumers' purchase behaviour in the National Capital Region, Philippines. *Theory*: UTAUT2
Preetha & Iswarya (2019)	Chennai	Food online order and delivery app	To estimate the factors influencing the intention to use food online order and delivery app via platforms. *Theory*: TAM
Lee, Lee & Jeon (2017)	Korea	Food delivery apps	To examine the relationship between the determinants that affect customers' use of food delivery apps. *Theory*: TAM

Author(s)	Country/ region	Area of study/ subject field	Purpose of study and theory adopted
Lee, Sung & Jeon (2019)	Korea	Food delivery apps	To analyse an extended UTAUT2 Model that augments information quality to identify the determinants of continuous use intention for food delivery software apps. *Theory*: UTAUT2
Muangmee, Kot, Meekaewkunchorn, Kassakorn & Khalid (2021)	Bangkok	Food delivery apps	To investigate the factors determining the behavioural intention of using food delivery apps during COVID-19 pandemics, under a case study of Bangkok, Thailand. *Theory*: UTAUT; Task-Technology Fit (TTF)
Rasli, Zulkefli, Salleh, Ghani, Razali & Idris (2020)	Malaysia	Online food delivery apps	To explore the determinants of the continuous use intention of online food delivery by extending the UTAUT2 Model with information quality. *Theory*: UTAUT2
Song, Ruan & Jeon (2021)	Korea	Food delivery apps	To provide an understanding of the process of consumers accepting an on-demand food-delivery app, and to establish the effect of marketing communication on outcomes related to consumer behaviour. *Theory*: TAM; AIDA
Troise, O'Driscoll, Tani & Prisco (2020)	Ireland/Italy	Online delivery apps	To analyse the main drivers of users' intention to use food delivery apps. *Theory*: TAM; TPB
Zhao & Bacao (2020)	China	Food delivery apps	To proposes a comprehensive model integrating UATUT, ECM and TTF with the trust factor and to examine users' continuance intention to use food delivery apps during the COVID-19 pandemic in China. *Theory*: UATUT; Expectancy Confirmation Model (ECM); Task-Technology Fit Model (TTF)
Mobile food service/order apps			
Ahn (2019)	USA	Mobile food service apps	To investigate the relationships between m-commerce application quality components, customer satisfaction and repeat usage intentions in the light of the m-commerce success model in the restaurant context.
Amin, Arefin, Sultana, Islam & Akhtar (2020)	Bangladesh	Mobile food ordering apps	To explore conformation and perceived usefulness associated with mobile food ordering apps in consideration of their impacts upon attitudes, satisfaction and intention to continuously use. *Theory*: Expectation-confirmation theory
Song, Jeon & Jeon (2017)	Korea	Mobile food delivery apps	To suggest a method to improve the service quality of delivery apps for relevant businesses and researchers by determining the influences of delivery app usage factors on customer satisfaction and reuse intention.
Yeo, Goh & Rezaei (2017)	Malaysia	Online food delivery services	To examine the structural relationship between convenience motivation, post-usage usefulness, hedonic motivation, price-saving orientation, time-saving orientation, prior

Author(s)	Country/ region	Area of study/ subject field	Purpose of study and theory adopted
			online purchase experience, consumer attitude and behavioural intention towards online food delivery services.
Online grocery shopping			
Kim (2021)	South Korea	Mobile grocery shopping apps	Grounded in Uses and Gratifications Theory and the Theory of Planned Behaviour, to investigate utilitarian motives, hedonic motives, experiential motives, attitudes, subjective norms, perceived behavioural control, purchase intention and purchase behaviour among mobile grocery app users in South Korea. *Theory:* Gratification theory; TPB
Pauzi, Tan, Muharam & Talib (2017)	Malaysia	Online grocery shopping	To explore the factors such as social influence, facilitating conditions, hedonic motivations, perceived risk and perceived trust that influence the consumer intention to purchase groceries online. *Theory*: UTAUT2

Source: Author's own compilation

ANNEXURE B: ETHICS CLEARANCE CERTIFICATE

UNISA university of south africa

UNISA DEPARTMENT OF MARKETING AND RETAIL MANAGEMENT ETHICS REVIEW COMMITTEE

Date 2020-03-30

Dear Mrs Claudette Rabie

Decision: Ethics Approval from 2020 - 2023

NHREC Registration # : (if applicable)

ERC Reference # : 2020_MRM_002

Name : Mrs Claudette Rabie

Student #: 50853244

Staff #: 90184009

Researcher(s): Mrs Claudette Rabie, 012 429 4581, vniekc@unisa.ac.za

Supervisors(s): Prof Johannes A Wiid, 012 429 8303, jwiid@unisa.ac.za
Prof Michael C Cant, 012 429 8303, cantmc@unisa.ac.za

Working title of research:

Modelling the factors influencing consumers' behavioural intention to use mobile location-based shopping apps

Qualification: Postgraduate degree

Thank you for the application for research ethics clearance by the Unisa Department of Marketing and Retail Management Ethics Review Committee for the above mentioned research. Ethics approval is granted for 3 years.

*The **low risk application** was **reviewed** by the Department of Marketing and Retail Management Ethics Review Committee on 23 March 2020 in compliance with the Unisa Policy on Research Ethics and the Standard Operating Procedure on Research Ethics Risk Assessment.*

The proposed research may now commence with the provisions that:

University of South Africa
Preller Street, Muckleneuk Ridge, City of Tshwane
PO Box 392 UNISA 0003 South Africa
Telephone: +27 12 429 3111 Facsimile: +27 12 429 4150
www.unisa.ac.za

1. The researcher(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
2. Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study should be communicated in writing to the Department of Marketing and Retail Management Research Ethics Committee.
3. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.
4. Any changes that can affect the study-related risks for the research participants, particularly in terms of assurances made with regards to the protection of participants' privacy and the confidentiality of the data, should be reported to the Committee in writing, accompanied by a progress report.
5. The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study. Adherence to the following South African legislation is important, if applicable: Protection of Personal Information Act, no 4 of 2013; Children's act no 38 of 2005 and the National Health Act, no 61 of 2003.
6. Only de-identified research data may be used for secondary research purposes in future on condition that the research objectives are similar to those of the original research. Secondary use of identifiable human research data require additional ethics clearance.
7. Minor changes suggested by the committee be amended on the Form 1.

Note:

*The reference number **2020_MRM_002** should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.*

Yours sincerely,

Signature
Chair of Department of
Marketing and Retail Management ERC
E-mail: bothmch@unisa.ac.za
Tel: (012) 429 4376

Signature
Executive Dean: College of Economic and
Management Sciences
E-mail: mogalmt@unisa.ac.za
Tel: (012) 429 4805

University of South Africa
Preller Street, Muckleneuk Ridge, City of Tshwane
PO Box 392 UNISA 0003 South Africa
Telephone: +27 12 429 3111 Facsimile: +27 12 429 4150
www.unisa.ac.za

ANNEXURE C: CONSTRUCTS, SCALE ITEMS AND ORIGINATING RESEARCH

VARIABLE 1: PERFORMANCE EXPECTANCY
Description: Performance expectancy is the degree to which using a technology will provide benefits to consumers in performing certain activities (Venkatesh et al., 2012: 159). It denotes the degree to which an individual perceives that using a technology would provide them with the benefits of performing specific activities in everyday situations (Huang & Kao, 2015:5).
Keywords identified/taken from the definition and literature
Useful; achieve; quickly; productivity; beneficial; importance

	Statement	Source	Original item	Scale used
1	[PE1] Using same-day delivery apps frees up time, allowing me to do something else, and therefore increases my productivity. (Q5.22)	Hew et al. (2015); Chopdar & Sivakumar (2019)	Using mobile apps increases my productivity.	7-point Likert scale
		Venkatesh et al. (2012)	Using the system increases my productivity	
2	[PE2] Using same-day delivery apps helps me accomplish my shopping goals faster. (Q5.50)	Venkatesh et al. (2012)	Using the system enables me to accomplish tasks more quickly.	
		Hew et al. (2015)	Using mobile apps helps me accomplish things more quickly.	
		Miladinovic & Xiang (2016)	To use m-shopping fashion apps helps me accomplish things more quickly.	
		Chopdar & Sivakumar (2019)	Using mobile shopping apps helps me accomplish things more quickly.	
3	[PE3] Using same-day delivery apps allow me to achieve things that are important to me while I wait for products to be delivered (Q5.9)	Chopdar & Sivakumar (2019)	Using mobile shopping apps increases my chances of achieving things that are important to me.	
		Venkatesh et al. (2012)	Using mobile Internet increases my chances of achieving things that are important to me. (Dropped)	

Statement		Source	Original item	Scale used
4	[PE4] Same-day delivery apps are beneficial to me. (Q5.59)	Yi et al. (2006)	Online purchasing will be beneficial to me.	5-point Likert scale
		Okumus & Bilgihan (2014)	The app can be beneficial to me.	Unknown
5	[PE5] I find same-day delivery apps useful in my daily life. (Q5.55)	Venkatesh et al. (2012)	I find mobile Internet useful in my daily life.	7-point Liker scale
		Hew et al. (2015)	I find mobile apps useful in my daily life.	
		Miladinovic & Xiang (2016)	I find using m-shopping fashion apps useful.	
		Chopdar & Sivakumar (2019)	I find mobile shopping apps useful in my daily life.	
6	[PE6] I can save time when I use same-day delivery apps to purchase products. (Q5.42)	Lee, Sung & Jeon (2019)	I can same time when I use food delivery apps for purchasing food.	5-point Likert scale

VARIABLE 2: EFFORT EXPECTANCY
Description: Effort expectancy refers to the degree of ease that can be associated with the use of a specific technology, device or system. It is believed that using a technology would be easy and convenient. It represents the use of a technology, device or service without additional efforts from the user or without encountering much difficulty (Sani et al., 2019: 363; Yun et al., 2013: 219). In the context of this research study, effort expectancy is considered a measure of ease associated with using a mobile app (Kim & Baek, 2017: 151) and thus refers to the extent to which users believe that their continued use of same-day delivery apps will be easy to use, clear, understandable and free of any effort.
Keywords identified/taken from the definition and literature
Easy; ease of use; convenient; free of effort; without effort; without difficulty; clear and understandable

	Statement	Source	Original item	Scale used
1	[EE1] Learning how to use same-day delivery apps is easy for me. (Q5.46)	Venkatesh et al. (2012)	Learning how to use mobile internet is easy for me.	7-point Likert scale
		Miladinovic & Xiang (2016)	Learning how to use m-shopping fashion apps is easy for me.	
		Lee, Sung & Jeon (2019)	Learning how to use food delivery apps for purchasing food is easy for me.	5-point Likert scale
2	[EE2] It is easy for me to become skilful in using same-day delivery apps. (Q5.36)	Venkatesh et al. (2012)	It is easy for me to become skilful at using mobile internet.	7-point Likert scale
		Miladinovic & Xiang (2016)	It is easy for me to become skilful at using m-shopping fashion apps.	
		Lee, Sung & Jeon (2019)	It is easy for me to become skilful at using food delivery apps for purchasing food.	5-point Likert scale
3	[EE3] I find same-day delivery apps easy to use. (Q5.29)	Venkatesh et al. (2012)	I find mobile internet easy to use.	7-point Likert scale
4	[EE4] The way in which I interact with same-day delivery apps is clear and understandable. (Q5.16)	Venkatesh et al. (2012)	My interaction with mobile Internet is clear and understandable.	
		Hew et al. (2015)	My interaction with mobile apps is clear and understandable.	

Statement		Source	Original item	Scale used
		Lee, Sung & Jeon (2019)	My interaction with food delivery apps for the purchase of food is clear and understandable.	5-point Likert scale
5	[EE5] Same-day delivery apps require minimal effort from me. (Q5.7)	Chong et al. (2012)	Using m-commerce requires minimal effort. (*Construct: Perceived ease of use*)	7-point Likert scale
		Palos-Sanchez et al. (2017)	Interacting with the location-based services for tourism does not require a lot of mental effort. (*Construct: Perceived ease of use*)	
		Roback & Wakefield (2013)	Interacting with the location-based application would not require a lot of mental effort. (*Construct: Perceived ease of use*)	

VARIABLE 3: FACILITATING CONDITIONS
Description: Facilitating conditions represent a user's perception that the necessary resources and support are available to perform a given behaviour (Venkatesh et al., 2012: 159). It is an individual's belief that organisational and technical infrastructure exists to support the use of the technology (Venkatesh et al., 2003: 453). From a technological point of view, facilitating conditions refer to the degree to which a user believes that technical infrastructure and operational support exist to help them successfully use the system or device whenever necessary (Baptista & Olivera, 2015: 421; Ho & Amin, 2019: 27; Huang & Kao, 2015: 6).
Keywords identified/taken from the definition and literature
Resources; support; organisational and technical infrastructure; operational support; knowledge; skills; abilities; help from others; content; compatible

	Statement	Source	Original item	Scale used
1	[FC1] I can get help from others when I have difficulties using same-day delivery apps. (Q5.13)	Venkatesh et al. (2012)	I can get help from others when I have difficulties using mobile internet.	7-point Likert scale
		Hew et al. (2015)	I can get help from others when I have difficulties using mobile apps.	
		Miladinovic & Xiang (2016)	I can get help from others when I have difficulties using m-shopping apps for fashion goods.	
2	[FC2] It is important that same-day delivery apps are compatible with other technologies I use (such as tablets or smart watches). (Q5.21)	Venkatesh et al. (2012)	Mobile internet is compatible with other technologies I use.	
		Hew et al. (2015)	Mobile apps are compatible with other technologies I use.	
		Miladinovic & Xiang (2016)	M-shopping fashion apps are compatible with other technologies I use.	
3	[FC3] I have the knowledge necessary to use same-day delivery apps. (Q5.47)	Venkatesh et al. (2012)	I have the knowledge necessary to use mobile internet.	
		Hew et al. (2015)	I have the knowledge necessary to use mobile apps.	
		Lee, Sung & Jeon (2019)	I have the knowledge necessary to use food delivery apps for purchasing food.	5-point Likert scale

Statement		Source	Original item	Scale used
4	[FC4] I have the resources necessary to use same-day delivery apps. (Q5.23)	Venkatesh et al. (2012)	I have the resources necessary to use mobile internet.	7-point Likert scale
		Hew et al. (2015)	I have the resources necessary to use mobile apps.	
		Miladinovic & Xiang (2016)	I have the resources necessary to use the m-shopping fashion app.	
5	[FC5] I feel comfortable using same-day delivery apps. (Q5.63)	Hew et al. (2015)	I feel comfortable using mobile apps.	
		Lee, Sung & Jeon (2019)	I feel comfortable using food delivery apps for purchasing food.	5-point Likert scale

VARIABLE 4: SOCIAL INFLUENCE
Description: Social influence occurs when individuals are predisposed by the thoughts, opinions, behaviours, attitudes and feelings that result from interactions with others, which are then considered to be socially acceptable behaviours, whether they be intentional or unintentional (Rashotte, n.d.). Individuals generally develop acceptance and usage intention towards a technology when encouraged and motivated by the people close to them and whose opinions they value. Social influences can be twofold as consumers being influenced either by mass media, such as newspapers, television, Internet and radio, or by their interpersonal influences, such as their relatives, peers, friends and colleagues (Chopdar et al., 2018: 113; Hew et al., 2015: 1273).
Keywords identified/taken from the definition and literature
Opinions; behaviours; attitudes; feelings; significant others; influence; important; recommend; suggest; mass media and interpersonal influences

	Statement	Source	Original item	Scale used
1	[SI1] People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps. (Q5.3)	Venkatesh et al. (2012)	People who are important to me think that I should use mobile internet.	7-point Likert scale
2	[SI2] People whose opinions I value use same-day delivery apps. (Q5.12)		People whose opinions that I value prefer that I use mobile internet.	
3	[SI3] People who influence my behaviour think that I should use same-day delivery apps. (Q5.26)		People who influence my behaviour think that I should use mobile Internet.	
4	[SI4] Friends' suggestions and recommendations affect my decision to use same-day delivery apps. (Q5.32)	Leong, Ooi, Chong & Lin (2013)	Friends' suggestions and recommendations will affect my decision to use m-entertainment.	5-point Likert scale
5	[SI5] Family members influence my decision to use same-day delivery apps. (Q5.38)	Chong et al. (2012)	Friends and family members have an influence on my decision to use m-commerce.	
6	[SI6] Mass media (such as TV, radio, magazines and social media) influence my decision to use same-day delivery apps. (Q5.54)	Chong et al. (2012)	Mass media (e.g. TV, radio, newspapers) will influence my decision to use m-commerce.	

VARIABLE 5: HEDONIC MOTIVATION
Description: Hedonic motivation refers to the fun or pleasure derived from using a technology (Venkatesh et al., 2012: 161). Hedonic shopping motivations, derived from perceived enjoyment, are an individual's motives for shopping based on emotional responses, sensory pleasures, dreams and aesthetic considerations (Kusuma et al., 2013: 242). From a mobile app point of view, hedonic motivations refer to the customer's need for pleasure, enjoyment or entertainment they can obtain from their engagement with a mobile app (Mavuya, 2016: 17).
Keywords identified/taken from the definition and literature
Perceived enjoyment; fun; pleasure; emotional responses; sensory pleasure; dreams; aesthetic consideration; enjoyment; entertainment

	Statement	Source	Original item	Scale used
1	[HM1] Using same-day delivery apps is fun. (Q5.34)	Venkatesh et al. (2012)	Using mobile internet is fun.	7-point Likert scale
2	[HM2] Using same-day delivery apps is enjoyable. (Q5.20)		Using mobile internet is enjoyable.	
3	[HM3] Using same-day delivery apps is very entertaining. (Q5.6)		Using mobile internet is very entertaining.	
4	[HM4] Using same-day delivery apps is interesting. (Q5.45)	Fang, Zhao, Wen & Wang (2017)	Using the travel app is interesting.	
5	[HM5] I experience pleasure when using same-day delivery apps. (Q5.56)	Indrawati & Haryoto (2015)	Feeling pleasure when using TV streaming services.	Unknown

VARIABLE 6: HABIT
Description: Habit is described as the degree to which individuals tend to perform a specific behaviour, or use specific technologies automatically, because of learning, and because of previous experiences (Venkatesh et al., 2012: 161). For the purpose of this study, habit is conceptualised as the extent to which the use of technology, due to learning, has become automatic, habituated and a natural occurrence to the user.
Keywords identified/taken from the definition and literature
Automatically; habitually; habituated; addicted; natural occurrence; must use; learned behaviour; previous experience

	Statement	Source	Original item	Scale used
1	[HA1] The use of same-day delivery apps has become a habit of mine. (Q5.2)	Venkatesh et al. (2012)	The use of mobile internet has become a habit for me.	7-point Likert scale
2	[HA2] I am addicted to using same-day delivery apps. (Q5.19)		I am addicted to using mobile internet.	
3	[HA3] I must use same-day delivery apps. (Q5.41)		I must use mobile internet.	
4	[HA4] Using same-day delivery apps has become second nature to me. (Q5.52)		Using mobile internet has become natural to me. *(Removed)*	

VARIABLE 7: PRICE VALUE
Description: Price value refers to consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost of using it (Venkatesh et al., 2012: 161). It entails the perceived benefits of using an app versus the monetary costs incurred in using the app (Lee et al., 2019: 4). Consumers therefore look for higher perceived benefits in comparison to the monetary sacrifice (Gupta et al., 2018: 58).
Keywords identified/taken from the definition and literature
Reasonable costs/prices; save money; value for money; specials; discounts; deals; lower prices; reasonably priced; value; benefits

	Statement	Source	Original item	Scale used
1	[PV1] The cost of using same-day delivery apps is reasonable. (Q5.25)	Gupta & Dogra (2017)	The cost of using mapping apps is reasonable.	5-point Likert scale
2	[PV2] Same-day delivery apps offer good value for money. (Q5.14)	Venkatesh et al. (2012)	Mobile Internet is reasonably priced.	7-point Likert scale
3	[PV3] At the current price for using same-day delivery apps (such as Internet/data costs and smartphone maintenance), good value for money is provided. (Q5.8)		Mobile Internet is good value for the money.	
			At the current price, mobile Internet provides a good value.	
		Miladinovic & Xiang (2016)	At the current price for using m-shopping fashion apps (such as internet, shopping maintenance, price of apps…) good value for money is provided.	
4	[PV4] Using same-day delivery apps is worth the cost involved, such as the delivery and service fees. (Q5.62)	Gupta & Dogra (2017)	Using mapping apps is worth the cost.	5-point Likert scale
5	[PV5] It is more expensive to purchase products through same-day delivery apps than physically going to the store. (Q5.64)	Self-developed		

VARIABLE 8: LIFESTYLE COMPATIBILITY
Description: Lifestyle compatibility is the natural alignment of lifestyle choices and values (Yang et al., 2021: 5) and refers to the degree to which individuals perceive that a particular technology is well suited to the way they think, act and lead their lives (Boateng et al., 2016: 471). From an online shopping perspective, lifestyle compatibility implies the beliefs and values that an individual holds with regard to shopping online, and how well the activity of shopping online fits into a specific consumer's lifestyle (Cuna, 2020: 9).
Keywords identified/taken from the definition and literature
Compatible; fits well; fits into; well-suited; essential; required

	Statement	Source	Original item	Scale used
1	[LSC1] Using same-day delivery apps fits well into my lifestyle. (Q5.61)	Belanche, Flavián & Pérez-Rueda (2020)	Using mobile apps fits well with my lifestyle.	7-point Likert scale
2	[LSC2] Same-day delivery apps fit well with how I like to do my shopping. (Q5.53)	Cuna (2020)	Shopping online fits well with how I like to do my shopping.	5-point Likert scale
3	[LSC3] Same-day delivery apps are compatible with most aspects of my shopping activities. (Q5.40)		Shopping online is compatible with most aspects of my shopping activities.	
4	[LSC4] I regularly order products through same-day delivery apps. (Q5.33)	Arora & Malik (2020)	I order food online on mobile apps.	7-point Likert scale
5	[LSC5] I prefer using same-day delivery apps instead of physically going to a store. (Q5.1)	Arora & Malik (2020)	I prefer to shop online than physically go to the stores	7-point Likert scale
6	[LSC6] The use of same-day delivery apps is a necessity in today's world. (Q5.11)		The usage of mobile apps is a necessity in today's world	
7	[LSC7] I cannot imagine my life without same-day delivery apps. (Q5.18)		I cannot imagine my life without mobile apps	
8	[LSC8] Same-day delivery apps are an important source of information for me. (Q5.37)		Mobile apps are an important source of information and entertainment for me.	
9	[LSC9] Life will be very boring without same-day delivery apps. (Q5.48)		Life will be very boring/dull without mobile apps	

VARIABLE 9: PERCEIVED RISK
Description: In the context of m-commerce, perceived risk is conceptualised as "… a potential loss as perceived by a customer while shopping online using mobile retail apps when compared to purchasing products offline" (Kaushik et al., 2020: 12). Pauzi et al. (2017: 5) report that perceived risk is also known as an individual's degree of doubt concerning the outcome of their decision in online purchasing.
Keywords identified/taken from the definition and literature
Risk; uncertainty; potential loss; doubt; safety; danger; apprehension

	Statement	Source	Original item	Scale used
1	[PR1] Providing personal information (such as my name, address and telephone number), on same-day delivery apps is risky. (Q5.58)	Fortes & Rita (2016)	Providing personal information (i.e. social security number and m other's maiden name) online is risky.	7-point Likert scale
2	[PR2] I am concerned that the information I submit on same-day delivery apps could be misused. (Q5.4)		I am concerned that the information I submit on the internet could be misused	
3	[PR3] I feel comfortable giving out payment information (such as credit card details) to make a transaction on same-day delivery apps. (Q5.17) *[Reverse scored]*	Amaro & Duarte (2015); Kaushik, Mohan & Kumar (2020)	I do not feel comfortable giving out credit card information to make a transaction over the internet	5-point Likert scale
4	[PR4] I feel apprehensive (anxious/nervous) about purchasing products/services through same-day delivery apps. (Q5.28)	Amaro & Duarte (2015); Kaushik et al. (2020)	I feel apprehensive about purchasing online	5-point Likert scale
5	[PR5] Purchasing products/services through same-day delivery apps is risky. (Q5.35)		Purchasing online is risky	
6	[PR6] There is too much uncertainty associated with purchasing products/services using same-day delivery apps. (Q5.51)		There is too much uncertainty associated with purchasing travel online	

	Statement	Source	Original item	Scale used
7	[PR7] The use of same-day delivery apps is riskier than other methods of purchasing products/ services (such as personally visiting a store). (Q5.60)		Compared with other methods of purchasing, shopping online is riskier.	
8	[PR8] I believe that the risk of purchasing products/services through same-day delivery apps is very high. (Q5.15)	Kaushik et al. (2020)	I believe that the risk of purchasing products online using a retail mobile app is very high	

VARIABLE 10: PERCEIVED SELF-EFFICACY
Description: From an organisational setting, self-efficacy is contextualised as "… the judgement of one's ability to use a technology to accomplish a particular job" (Venkatesh et al., 2003: 432). In the context of this study, perceived self-efficacy signifies an individual's belief or perception in their own ability and self-confidence to complete a specific activity or task using mobile technology (Hu & Zhang, 2016: 645; Yul, 2014: 12). Perceived self-efficacy represents a person's belief concerning their own capacity to carry out a specific task using technology or mobile devices, which is argued to significantly predict behavioural intention and adoption behaviours (Singh et al., 2018: 115).
Keywords identified/taken from the definition and literature
Ability to accomplish; belief; perception; self-confidence; abilities or skills; knowledge; independent; confidence

	Statement	Source	Original item	Scale used
1	[PSE1] I can use same-day delivery apps without the help of others. (Q5.10)	Singh, Zolkepli & Kit (2018)	I am able to use mobile commerce services without the help of others.	7-point Likert scale
		Hu & Zhang (2016)	I can use m-library apps successfully without other's help	5-point Likert scale
		Yul (2014)	I am able to use a mobile fitness app without the help of others	6-point Likert scale
2	[PSE2] I have enough knowledge and skills to use same-day delivery apps successfully. (Q5.30)	Singh et al. (2018)	I have the knowledge and skills required to use mobile commerce services	7-point Likert scale
		Hu & Zhang (2016)	I have enough knowledge and skills to use m-library apps successfully	5-point Likert scale
		Yul (2014)	I have knowledge and skills required to use a mobile fitness app	6-point Likert scale
3	[PSE3] I am confident that I can use same-day delivery apps successfully. (Q5.24)	Hu & Zhang (2016)	I am confident to use m-library apps successfully	5-point Likert scale

Statement		Source	Original item	Scale used
4	[PSE4] I can use same-day delivery apps reasonably well on my own. (Q5.44)	Singh et al. (2018)	I am able to use mobile commerce services reasonably well on my own	7-point Likert scale
		Yul (2014)	I am able to use a mobile fitness app reasonably well on my own	6-point Likert scale
5	[PSE5] Overall, I am confident in using same-day delivery apps by myself. (Q5.49)		Overall, I am confident in using a mobile fitness app by myself	

VARIABLE 11: ATTITUDE TOWARDS USE
Description: Attitude "… is a person's enduring favourable or unfavourable evaluation, emotional feelings, and action tendencies towards the same object or idea" (Kotler, 2000: 175). In the context of consumer behaviour, consumer attitudes are defined as "… the consistent tendency of consumers to behave, favourably or unfavourably, with regards to a specific product or brand" (Schiffman & Kanuk, 2004: 253).
Keywords identified/taken from the definition and literature
Knowledge; experience; perceptions; beliefs; thoughts; attributes; opinions Emotions; like/dislike; enjoyment; feelings; emotional response

	Statement	Source	Original item	Scale used
1	[ATT1] Using same-day delivery apps is a smart way to shop. (Q5.27)	Kumar & Mukherjee (2013)	Mobile shopping would be a wise way to shop.	5-point Likert scale
		Venkatesh et al. (2003)	Using the system is a foolish/wise idea.	7-point Likert scale
		Troise, O'Driscoll, Tani & Prisco (2021)	I think that using online food delivery would be a wise idea	
		Hu & Zhang (2016)	Using m-library apps is a wise idea	5-point Likert scale
2	[ATT2] I like using same-day delivery apps. (Q5.5)	Kumar & Mukherjee (2013)	I would not like to use my mobile device for shopping.	5-point Likert scale
		Venkatesh et al. (2003)	I like working with the system.	7-point Likert scale
		Yeow, Yuen, Tong & Lim (2008)	I like working with OBS	5-point Likert scale

Statement		Source	Original item	Scale used
3	[ATT3] Using same-day delivery apps is a good idea. (Q5.39)	Venkatesh et al. (2003)	Using the system is a good/bad idea.	7-point Likert scale
		Yeow et al. (2008)	It is a good idea to use OBS in my daily life	5-point Likert scale
		Troise et al. (2021)	I think that using online food delivery is a good idea	7-point Likert scale
4	[ATT4] Overall, I am satisfied with same-day delivery apps. (Q5.31)	Hu & Zhang (2016)	On the whole, I am satisfied with m-library apps	5-point Likert scale
5	[ATT5] In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services. (Q5.43)	Troise et al. (2021)	In my opinion, it is desirable to use online food delivery	7-point Likert scale
		Cho, Bonn & Li (2018)	I desire to use the delivery app when I purchase food	
6	[ATT6] I am in favour of purchasing products/ services through same-day delivery apps. (Q5.57)		I am strongly in favour of ordering food through the delivery app	

DEPENDENT VARIABLE: BEHAVIOURAL INTENTION				
Description: Behavioural intention is defined as "… a person's likelihood or subjective probability to engage in a given behaviour" (CHIRr, n.d.). Seminal author Icek Ajzen (1991: 181) argues that behavioural intention reflects how hard a person is willing to try and how motivated they are to perform a given behaviour.				
Keywords identified/taken from the definition and literature				
Useful; achieve; quickly; productivity; beneficial; importance				
	Statement	**Source**	**Original item**	**Scale used**
1	[BI1] I intend to continue using same-day delivery apps in the future.	Venkatesh et al. (2003; 2012)	I intend to continue using mobile internet in the future.	7-point Likert scale
2	[BI2] I plan to continue using same-day delivery apps frequently.		I plan to continue to use mobile internet frequently.	
3	[BI3] I will always try to use same-day delivery apps in my daily life.		I will always try to use mobile internet in my daily life.	
4	[BI4] My intentions are to continue using same-day delivery apps than to use any alternative means.	Chopdar & Sivakumar (2019)	My intention is to continue using mobile shopping apps rather than discontinue its use.	
5	[BI5] I will recommend the use of same-day delivery apps to others.		I will recommend use of mobile shopping apps to others.	
6	[BI6] I intend to use same-day delivery apps more frequently going forward.	Self-developed	N/A	N/A

ANNEXURE D: RESEARCH INSTRUMENT

Ethics clearance #: 2020_MRM_002

INFORMED CONSENT DOCUMENT:

PARTICIPANT INFORMATION SHEET FOR AN ANONYMOUS WEB-BASED SURVEY

Dear prospective participant

You are invited to participate in an academic research study of Mrs Claudette Rabie, a PhD student in Management Studies at the Department of Marketing and Retail Management, University of South Africa (UNISA).

The title of the study is "*Investigating the factors that influence South African consumers' behavioural intention to continue using same-day delivery apps".* The study is aimed at achieving a better understanding of the factors that influence consumers' behavioural intention to continuously accept and use same-day delivery apps (applications).

It is anticipated that the study will yield important findings about the factors that influence consumers to continually accept and use same-day delivery apps. It is furthermore expected that the study will provide a better understanding of the key determinants of consumers' acceptance and use of these apps with a view to offer more effective and successful same-day delivery apps in a South African context. From a theoretical perspective, examining the factors that influence consumers' behavioural intention to accept and use same-day delivery apps will not only broaden our understanding of behavioural intention in a South African context, but also respond to Venkatesh, Thong and Xu's (2012) call to extend the UTAUT2 model to improve the predictive and explanatory power of the model. It is further anticipated that the research will make a valuable theoretical contribution to literature on behavioural intention and adoption behaviour by explicating the determinants of acceptance in a South African context.

You are, however, under no obligation to complete the questionnaire and you can withdraw from the study at any time before submitting the questionnaire. The questionnaire is anonymous,

meaning that we will have no way of connecting the information that you provide to you personally. The researcher furthermore undertakes to keep any information provided confidential. Only the researcher and the statistical analyst will have access to the data.

If you choose to participate in this survey, it will take no more than **20 minutes** of your time. Although you will not personally benefit from your participation in this study, it is envisioned that the findings of the study will contribute towards the existing body of knowledge on the factors that influence consumers to continually accept and use same-day delivery apps. The findings of this study will further benefit marketing managers, retailers, and mobile app developers in that they will be able to identify the key determinants of behavioural intention, allowing them to develop an effective and successful same-day delivery app for the South African consumer. We do not foresee that you will experience any negative consequences if you complete the questionnaire, and you do not have to incur any costs to participate in the study. You will not be reimbursed or receive any incentive for participating in this study.

By completing the questionnaire for this study, you agree that the information you provide may be used for research purposes, including dissemination through peer-reviewed publications and conference proceedings. Interested participants may obtain a copy of the completed thesis, or articles, from the primary researcher.

All records will be kept for five years for auditing purposes, after which they will be permanently destroyed. No hard copies will be available since the data collection will be completed electronically. Future use of the stored data will be subject to further ethics reviews and approval, if applicable.

The Ethics Committee of the Department of Marketing and Retail Management has reviewed and approved the proposed research. You may obtain a copy of the approval letter from the primary researcher if you so wish. The primary researcher, Mrs C Rabie, can be contacted by e-mail at vniekc@unisa.ac.za. Should you have any questions regarding the ethical aspects of the study, you can e-mail the chairperson of the Department's Ethics Committee, Dr CH Bothma on bothmch@unisa.ac.za. Alternatively, you can report any serious unethical behaviour at the University's Toll-Free Hotline, 0800 86 96 93.

If you are willing to participate in this study, kindly access the online questionnaire by clicking on the following link: **https://www.research.net/r/RYDDQH7**

Kind regards,
Mrs Claudette Rabie
Tel: 012 429 4581 / 071 871 2215
e-mail: vniekc@unisa.ac.za

INFORMED CONSENT

By agreeing to participate in this study, you confirm that the person asking your consent to take part in this research has informed you about the nature, procedure, potential benefits, and anticipated inconvenience of participation (see details in the informed consent document).

You also agree to the following:

1. You have read and understood the study as explained in the participation information letter that invited you to participate.
2. You have been provided with the contact details of the researcher and have sufficient opportunity to ask questions if the need arises.
3. You understand that your participation is voluntary and that you are free to withdraw at any time before submitting the survey, without penalty.
4. You are aware that the findings of this study will be anonymously processed into a research report, journal publications and/or conference proceedings but that your participation will be kept confidential.
5. You understand your rights in relation to your participation in this research study and confirm that you are between the ages of 18 and 65 years.

To confirm your consent to participate in the study and continue with the survey, click on **NEXT**.

INSTRUCTIONS

The survey consists of several questions that measure your opinion about and use of same-day delivery apps.

Please read each instruction and statement carefully before selecting the most accurate option that represents your view. There are no right or wrong answers to these questions. The researcher is only interested in your personal opinions. The “right” answer to any question is your sincere and truthful response.

Remember that your response will remain completely confidential and will be used for research purposes only. The research report compiled from the data obtained will include an integrated summary of the results. No individual can or will be identified by name when the findings are reported.

The survey consists of the following sections:

Section A: General information
Section B: Factors that influence behavioural intention
Section C: Behavioural intention and use behaviour
Section D: Biographical information

It will take approximately 20 minutes of your time to complete the survey.

Please answer all the questions. This is extremely important as questionnaires that are only partly or inaccurately completed will have to be excluded from the analyses.

Thank you for participating in this important research project.

SCREENING QUESTIONS

You must comply with certain criteria to be able to provide valuable information for this study and, therefore, to qualify to participate in the survey. Kindly answer the following screening questions before continuing with the survey.

Question 1: Do you reside in the province of Gauteng, KwaZulu-Natal or the Western Cape in South Africa?

Yes	1	→ **Continue to question 2.**
No	2	→ **Unfortunately, you do not qualify to partake in this study.**

Question 2: Do you make use of a same-day delivery mobile applications (apps)? These include mobile apps of any retailer from which products are delivered on the same day on which the order was placed.

Same-day delivery applications (apps) are *mobile apps* by which customers order products or services that they will receive the day on which they placed the order on the mobile app. For example, when you order products on the mobile app during the day, they are delivered to your chosen address *on the same day*, within a few hours after you have placed your order on the specific mobile app.

Same-day delivery apps include, among others, Checkers Sixty60, Pick n Pay ASAP! (Bottles), Woolies Dash, OneCart, Uber Eats, Dischem DeliverD, Mr D Food, McDelivery, OrderIn, Quench, or Zulzi.

Yes	1	→ **Continue to Section A.**
No	2	→ **Unfortunately, you do not qualify to partake in this study.**

SECTION A: GENERAL INFORMATION

Kindly complete the following questions regarding your use of same-day delivery apps.

QUESTION 3

Indicate which of the following same-day delivery mobile apps you make use of to purchase products. *Mark all applicable options.*

Same-day delivery app		
3.1	Bottles Alcohol Delivery	1
3.2	Burger King	2
3.3	CartRun	3
3.4	Checkers Sixty60	4
3.5	Debonairs Pizza	5
3.6	Deliveroo	6
3.7	Dis-Chem DeliverD	7
3.8	Fishaways	8
3.9	iStore (*same-day delivery option only*)	9
3.10	KFC Delivery	10
3.11	Krispy Kreme	11
3.12	McDelivery (McDonald's)	12
3.13	Mr D Food	13
3.14	Nando's	14
3.15	Ocean Basket	15
3.16	OneCart	16
3.17	OrderIn	17
3.18	Pekkish SA	18
3.19	Pick n Pay ASAP! (Bottles)	19
3.20	Pizza Hut	20
3.21	Quench	21
3.22	Simply Asia	22
3.23	Steers	23
3.24	Stulo	24
3.25	Takealot.com (*same-day delivery option only*)	25
3.26	The Dog Food App	26
3.27	Thirst Busters – On-demand alcohol delivery	27
3.28	Uber Eats	28
3.29	Woolies Dash	29
3.30	Zomato	30
3.31	Zulzi	31
3.32	Other*	32

*If "other" was selected, please specify: _____

QUESTION 4

Indicate how **often** you use same-day delivery apps for the following reasons/activities.

Statement: I use same-day delivery apps …		**Never**	**Rarely**	**Occasionally**	**Frequently**	**Always**
4.1	to purchase products.	1	2	3	4	5
4.2	to acquire services.	1	2	3	4	5
4.3	to browse for specials, deals or discounts.	1	2	3	4	5
4.4	to collect or use coupons or vouchers.	1	2	3	4	5
4.5	to benefit from online-only deals or specials.	1	2	3	4	5
4.6	to compare prices.	1	2	3	4	5
4.7	to compare products.	1	2	3	4	5
4.8	to compare services.	1	2	3	4	5
4.9	to check product availability.	1	2	3	4	5
4.10	to share product details with others (such as peers, friends or family members).	1	2	3	4	5
4.11	to find the contact details of a specific retailer.	1	2	3	4	5
4.12	to give reviews.	1	2	3	4	5
4.13	to read reviews.	1	2	3	4	5
4.14	to find a store closest to you.	1	2	3	4	5
4.15	to avoid having to physically go to a store.	1	2	3	4	5
4.16	to maintain social distancing because of the COVID-19 pandemic.	1	2	3	4	5
4.17	because it is convenient to have products delivered to my door.	1	2	3	4	5
4.18	because it is safer than having to physically go to the store.	1	2	3	4	5

SECTION B: FACTORS THAT INFLUENCE BEHAVIOURAL INTENTION

QUESTION 5

Keep the following explanation of same-day delivery apps in mind when you answer the questions below:

Same-day delivery applications (apps) are *mobile apps* by which customers order products or services that they will receive the day on which they placed the order on the mobile app. For example, when you order products on the mobile app during the day, they are delivered to your chosen address *on the same day*, within a few hours after you have placed your order on the specific app.

Same-day delivery apps include, among others, Checkers Sixty60, Pick n Pay ASAP! (Bottles), Woolies Dash, OneCart, Uber Eats, Mr D Food, Dischem DeliverD, McDelivery, OrderIn, Quench, and Zulzi.

Indicate the extent to which you disagree or agree with the following statements regarding **same-day delivery apps**, as per the above explanation.

Statement		Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
5.1	I prefer using a same-day delivery app instead of physically going to a store.	1	2	3	4	5
5.2	The use of same-day delivery apps has become a habit of mine.	1	2	3	4	5
5.3	People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps.	1	2	3	4	5
5.4	I am concerned that the information I submit on same-day delivery apps could be misused.	1	2	3	4	5
5.5	I like using same-day delivery apps.	1	2	3	4	5
5.6	Using same-day delivery apps is very entertaining.	1	2	3	4	5
5.7	Same-day delivery apps require minimal effort from me.	1	2	3	4	5
5.8	At the current price for using same-day delivery apps (such as internet/data costs, and smartphone maintenance), good value for money is provided.	1	2	3	4	5
5.9	Using same-day delivery apps allows me to achieve things that are important to me while I wait for products to be delivered.	1	2	3	4	5
5.10	I can use same-day delivery apps without the help of others.	1	2	3	4	5
5.11	The use of same-day delivery apps is a necessity in today's world.	1	2	3	4	5

Statement		Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
5.12	People whose opinions I value use same-day delivery apps.	1	2	3	4	5
5.13	I can get help from others when I have difficulties using same-day delivery apps.	1	2	3	4	5
5.14	Same-day delivery apps offer good value for money.	1	2	3	4	5
5.15	I believe that the risk of purchasing products/services through same-day delivery apps is very high.	1	2	3	4	5
5.16	The way I interact with same-day delivery apps is clear and understandable.	1	2	3	4	5
5.17	I feel comfortable giving out payment information (such as credit card details) to transact on a same-day delivery app.	1	2	3	4	5
5.18	I cannot imagine my life without same-day delivery apps.	1	2	3	4	5
5.19	I am addicted to using same-day delivery apps.	1	2	3	4	5
5.20	Using same-day delivery apps is enjoyable.	1	2	3	4	5
5.21	Same-day delivery apps are compatible with other technologies I use.	1	2	3	4	5
5.22	Using same-day delivery apps frees up time, allowing me to do something else, and therefore increases my productivity.	1	2	3	4	5
5.23	I have the resources necessary to use same-day delivery apps.	1	2	3	4	5
5.24	I am confident that I can use same-day delivery apps successfully.	1	2	3	4	5
5.25	The cost of using same-day delivery apps is reasonable.	1	2	3	4	5
5.26	People who influence my behaviour think that I should use same-day delivery apps.	1	2	3	4	5
5.27	Using same-day delivery apps is a smart way to shop.	1	2	3	4	5
5.28	I feel apprehensive (anxious/nervous) about purchasing products/services through same-day delivery apps.	1	2	3	4	5
5.29	I find same-day delivery apps easy to use.	1	2	3	4	5
5.30	I have enough knowledge and skills to use same-day delivery apps successfully.	1	2	3	4	5
5.31	Overall, I am satisfied with same-day delivery apps.	1	2	3	4	5
5.32	Friends' suggestions and recommendations affect my decision to use same-day delivery apps.	1	2	3	4	5
5.33	I regularly order products through same-day delivery apps.	1	2	3	4	5
5.34	Using same-day delivery apps is fun.	1	2	3	4	5
5.35	Purchasing products/services through same-day delivery apps is risky.	1	2	3	4	5
5.36	It is easy for me to become skilful in using same-day delivery apps.	1	2	3	4	5
5.37	Same-day delivery apps are an important source of information for me.	1	2	3	4	5
5.38	Family members influence my decision to use same-day delivery apps.	1	2	3	4	5

Statement		Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
5.39	Using same-day delivery apps is a good idea.	1	2	3	4	5
5.40	Same-day delivery apps are compatible with most aspects of my shopping activities.	1	2	3	4	5
5.41	I must use same-day delivery apps.	1	2	3	4	5
5.42	I can save time when I use same-day delivery apps to purchase products.	1	2	3	4	5
5.43	In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services.	1	2	3	4	5
5.44	I can use same-day delivery apps reasonably well on my own.	1	2	3	4	5
5.45	Using same-day delivery apps is interesting.	1	2	3	4	5
5.46	Learning how to use same-day delivery apps is easy for me.	1	2	3	4	5
5.47	I have the knowledge necessary to use same-day delivery apps.	1	2	3	4	5
5.48	Life will be very boring without same-day delivery apps.	1	2	3	4	5
5.49	Overall, I am confident in using same-day delivery apps by myself.	1	2	3	4	5
5.50	Using same-day delivery apps helps me accomplish my shopping goals faster.	1	2	3	4	5
5.51	There is a lot of uncertainty associated with purchasing products/services using same-day delivery apps.	1	2	3	4	5
5.52	Using same-day delivery apps has become second nature to me.	1	2	3	4	5
5.53	Same-day delivery apps fit in well with how I like to do my shopping.	1	2	3	4	5
5.54	Mass media (such as TV, radio, magazines and social media) influence my decision to use same-day delivery apps.	1	2	3	4	5
5.55	I find same-day delivery apps useful in my daily life.	1	2	3	4	5
5.56	I experience pleasure when using same-day delivery apps.	1	2	3	4	5
5.57	I am in favour of purchasing products/services through same-day delivery apps.	1	2	3	4	5
5.58	Providing personal information (such as my name, address and telephone number) on same-day delivery apps is risky.	1	2	3	4	5
5.59	Same-day delivery apps are beneficial to me.	1	2	3	4	5
5.60	The use of same-day delivery apps is riskier than other methods of purchasing products/services (such as personally visiting a store).	1	2	3	4	5
5.61	Using same-day delivery apps fits well into my lifestyle.	1	2	3	4	5
5.62	Using a same-day delivery app is worth the costs involved, such as the delivery and service fees.	1	2	3	4	5
5.63	I feel comfortable using same-day delivery apps.	1	2	3	4	5
5.64	It is more expensive to purchase products through same-day delivery apps than physically going to the store.	1	2	3	4	5

SECTION C: BEHAVIOURAL INTENTION AND USE BEHAVIOUR

QUESTION 6

Indicate the extent to which you disagree or agree with the following statements regarding **planned usage behaviour** in respect of same-day delivery apps.

Statement		Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
6.1	I intend to continue using same-day delivery apps in the future.	1	2	3	4	5
6.2	I plan to continue using same-day delivery apps frequently.	1	2	3	4	5
6.3	I will always try to use same-day delivery apps in my daily life.	1	2	3	4	5
6.4	I intend to continue using same-day delivery apps rather than using any alternative means.	1	2	3	4	5
6.5	I will recommend the use of same-day delivery apps to others.	1	2	3	4	5
6.6	I intend to use same-day delivery apps more frequently going forward.	1	2	3	4	5

QUESTION 7

Indicate, using the scale below, how **frequently** (i.e. weekly) you use each of the following technologies and/or platforms.

Statement		Never	Rarely	Occasionally	Frequently	Always
7.1	Online shopping websites	1	2	3	4	5
7.2	Same-day delivery apps, such as Checkers Sixty60, Woolies Dash, and Pick n Pay Bottles.	1	2	3	4	5
7.3	Mobile shopping apps, such as Takealot.com, Woolworths, Truworths, Mr Price, Clicks, Superbalist, Zando and Wish.	1	2	3	4	5
7.4	Grocery apps, such as Pick n Pay and Woolworths.	1	2	3	4	5
7.5	Fast-food delivery services, such as Uber Eats, Mr D Food and OrderIn.	1	2	3	4	5

SECTION D: BIOGRAPHICAL INFORMATION

Please complete the following questions regarding your biographical information.

QUESTION 8

How do you identify yourself?

Female	1
Male	2
Prefer not to say	3
Other*	4

*If “other” was selected, please specify: _____

QUESTION 9

Indicate the period in which you were born.

Before 1930	1
1930–1949	2
1950–1969	3
1970–1989	4
1990–2000	5
2001–2003	6

QUESTION 10

What is your current age (in years, e.g., 32)?

QUESTION 11

In which province of South Africa do you reside?

Gauteng	1
Kwa-Zulu Natal	2
Western Cape	3
Prefer not to say	4
Other*	5

*If “other” was selected, please specify: _____

QUESTION 12

Indicate your ethnic orientation.

Asian	1
Black	2
Coloured	3
Indian	4
White	5
Prefer not to say	6
Other*	7

*If “other” was selected, please specify: _____

Thank you for your participation in the study. Should you have any queries regarding the purpose of the study, or the survey instrument, please e-mail the researcher, Mrs Claudette Rabie, at vniekc@unisa.ac.za.

ANNEXURE E: PILOT STUDY RESULTS – RELIABILITY AND ITEM-TOTAL STATISTICS

Pilot study results: Reliability statistics

Construct	No. of items	Cronbach's alpha
Performance expectancy	6	0.836
Effort expectancy	5	0.709
Facilitating conditions	5	0.442
Social influence	6	0.837
Hedonic motivation	5	0.859
Habit	4	0.767
Price value	5	0.499
Lifestyle compatibility	9	0.887
Perceived risk	8	0.696
Perceived self-efficacy	5	0.897
Attitude towards use	6	0.813
Behavioural intention	6	0.897

Pilot study results: Item-total statistics

Code	Scale item	Scale mean if deleted	Scale variance if deleted	Corrected item – total correlation	Squared multiple correlations	Cronbach's alpha if item deleted
Performance expectancy						
PE1	Using same-day delivery apps frees up time, allowing me to do something else, and therefore increases my productivity.	20.35	9.123	0.696	0.721	0.796
PE2	Using same-day delivery apps helps me accomplish my shopping goals faster.	20.54	8.422	0.636	0.466	0.805
PE3	Using same-day delivery apps allows me to achieve things that are important to me while I wait for products to be delivered.	20.46	9.089	0.618	0.521	0.808
PE4	Same-day delivery apps are beneficial to me.	20.62	9.408	0.602	0.581	0.812
PE5	I find same-day delivery apps useful in my daily life.	20.62	8.853	0.550	0.473	0.824
PE6	I can save time when I use same-day delivery apps to purchase products.	20.51	8.979	0.595	0.600	0.813
Effort expectancy						
EE1	Learning how to use same-day delivery apps is easy for me.	16.97	3.916	0.741	0.578	0.575
EE2	It is easy for me to become skilful in using same-day delivery apps.	17.22	3.785	0.398	0.393	0.701
EE3	I find same-day delivery apps easy to use.	17.03	4.694	0.360	0.195	0.700
EE4	The way in which I interact with same-day delivery apps is clear and understandable.	17.19	4.380	0.439	0.218	0.673
EE5	Same-day delivery apps require minimal effort from me.	17.43	3.363	0.516	0.347	0.646
Facilitating conditions						
FC1	I can get help from others, such as friends or family members, when I have difficulties using same-day delivery apps.	17.43	3.308	0.101	0.101	0.588
FC2	It is important that same-day delivery apps are compatible with other technologies I use (such as tablets or smartwatches).	13.38	2.242	0.231	0.187	0.632
FC3	I have the necessary knowledge to use same-day delivery apps.	12.97	1.749	0.531	0.507	0.371
FC4	I have the necessary resources (such as smartphone capabilities, WiFi access and mobile data) to use same-day delivery apps.	12.86	2.231	0.464	0.435	0.463
FC5	I feel comfortable using same-day delivery apps.	13.08	2.243	0.300	0.333	0.568

Code	Scale item	Scale mean if deleted	Scale variance if deleted	Corrected item – total correlation	Squared multiple correlations	Cronbach's alpha if item deleted
	Social influence					
SI1	People who are important to me, such as friends, family members and peers, think I should use same-day delivery apps.	14.89	18.321	0.627	0.547	0.808
SI2	People whose opinions I value use same-day delivery apps.	14.59	19.137	0.552	0.363	0.822
SI3	People who influence my behaviour think that I should use same-day delivery apps.	15.22	18.396	0.652	0.477	0.804
SI4	Friends' suggestions and recommendations affect my decision to use same-day delivery apps.	15.19	18.380	0.662	0.569	0.802
SI5	Family members influence my decision to use same-day delivery apps.	15.35	16.845	0.751	0.706	0.781
SI6	Mass media (such as TV, radio, magazines and social media) influence my decision to use same-day delivery apps.	15.16	19.195	0.455	0.290	0.845
	Hedonic motivation					
HM1	Using same-day delivery apps is fun.	13.38	8.575	0.790	0.661	0.811
HM2	Using same-day delivery apps is enjoyable.	13.43	8.752	0.606	0.417	0.846
HM3	Using same-day delivery apps is very entertaining.	13.84	7.751	0.602	0.463	0.855
HM4	Using same-day delivery apps is interesting.	13.27	7.703	0.788	0.704	0.799
HM5	I experience pleasure when using same-day delivery apps.	13.43	7.808	0.660	0.594	0.834
	Habit					
HA1	The use of same-day delivery apps has become a habit of mine.	8.49	6.146	0.535	0.303	0.731
HA2	I am addicted to using same-day delivery apps.	9.95	5.941	0.605	0445	0.691
HA3	I must use same-day delivery apps.	8.92	6.243	0.622	0.452	0.685
HA4	Using same-day delivery apps has become second nature to me.	8.24	6.745	0.516	0.290	0.738
	Price value					
PV1	The cost of using same-day delivery apps is reasonable.	22.68	6.892	0.341	0.482	0.416
PV2	Same-day delivery apps offer good value for money.	22.89	6.710	0.459	0.474	0.372
PV3	At the current price for using same-day delivery apps (such as internet/data costs, and smartphone maintenance), good value for money is provided.	22.68	7.225	0.372	0.368	0.415
PV4	Using a same-day delivery app is worth the cost involved, such as the delivery and service fees.	22.70	6.715	0.507	0.470	0.360

Code	Scale item	Scale mean if deleted	Scale variance if deleted	Corrected item – total correlation	Squared multiple correlations	Cronbach's alpha if item deleted
PV5	It is more expensive to purchase products through same-day delivery apps than physically going to the store.	23.08	9.077	-0.160	0.229	0.646
(Item removed)	I can save money by using same-day delivery apps by comparing the prices offered at different stores.	22.81	7.324	0.262	0.422	0.452
(Item removed)	I like to search for cheap deals/specials at different stores when I use same-day delivery apps.	22.89	6.932	0.172	0.349	0.504
Lifestyle compatibility						
LSC1	Using same-day delivery apps fits well into my lifestyle.	28.81	33.435	0.726	0.699	0.870
LSC2	Same-day delivery apps fit in well with how I like to do my shopping.	29.11	31.877	0.783	0.672	0.863
LSC3	Same-day delivery apps are compatible with most aspects of my shopping activities.	29.05	34.664	0.583	0.467	0.879
LSC4	I regularly order products through same-day delivery apps.	29.03	32.360	0.650	0.644	0.874
LSC5	I prefer using a same-day delivery app instead of physically going to a store.	28.97	34.194	0.575	0.420	0.880
LSC6	The use of same-day delivery apps is a necessity in today's world.	28.46	34.477	0.565	0.429	0.881
LSC7	I cannot imagine my life without same-day delivery apps.	29.68	30.503	0.752	0.728	0.865
LSC8	Same-day delivery apps are an important source of information for me.	29.43	33.141	0.544	0.551	0.884
LSC9	Life will be very boring without same-day delivery apps.	29.73	31.869	0.626	0.527	0.877
Perceived risk						
PR1	Providing personal information (such as my name, address and telephone number) on same-day delivery apps is risky.	17.32	22.059	0.714	0.743	0.764
PR2	I am concerned that the information I submit on same-day delivery apps could be misused.	17.43	25.474	0.408	0.467	0.810
PR3	I feel comfortable giving out payment information (such as credit card details) to transact on a same-day delivery app.	17.68	26.059	0.431	0.375	0.806
PR4	I feel apprehensive (anxious/nervous) about purchasing products/ services through same-day delivery apps.	18.03	24.249	0.630	0.630	0.780
PR5	Purchasing products/services through same-day delivery apps is risky.	17.68	22.725	0.701	0.690	0.767
PR6	There is a lot of uncertainty associated with purchasing products/services using same-day delivery apps.	17.65	24.179	0.477	0.384	0.802
PR7	The use of same-day delivery apps is riskier than other methods of purchasing products/services (such as personally visiting a store).	17.46	23.589	0.531	0.628	0.793

Code	Scale item	Scale mean if deleted	Scale variance if deleted	Corrected item – total correlation	Squared multiple correlations	Cronbach's alpha if item deleted
PR8	I believe that the risk of purchasing products/services through same-day delivery apps is very high.	17.89	26.766	0.369	0.533	0.813
Perceived self-efficacy						
PSE1	I can use same-day delivery apps without the help of others.	18.00	4.222	0.677	0.609	0.891
PSE2	I have enough knowledge and skills to use same-day delivery apps successfully.	18.11	4.266	0.793	0.784	0.865
PSE3	I am confident that I can use same-day delivery apps successfully.	18.16	4.140	0.722	0.636	0.869
PSE4	I can use same-day delivery apps reasonably well on my own.	18.19	3.991	0.773	0.726	0.869
PSE5	Overall, I am confident in using same-day delivery apps by myself.	18.03	4.416	0.730	0.631	0.879
Attitude towards use						
ATT1	Using same-day delivery apps is a smart way to shop.	19.84	6.973	0.691	0.502	0.759
ATT2	I like using same-day delivery apps.	19.81	8.435	0.259	0.110	0.848
ATT3	Using same-day delivery apps is a good idea.	19.78	7.619	0.604	0.402	0.781
ATT4	Overall, I am satisfied with same-day delivery apps.	19.68	7.503	0.688	0.607	0.768
ATT5	In my opinion, it is better to use same-day delivery apps than other methods of purchasing products/services.	20.38	6.520	0.558	0.352	0.796
ATT6	I am in favour of purchasing products/services through same-day delivery apps.	19.97	6.360	0.761	0.685	0.738
Behavioural intention						
BI1	I intend to continue using same-day delivery apps in the future.	18.59	15.914	0.511	0.592	0.911
BI2	I plan to continue using same-day delivery apps frequently.	18.76	14.411	0.818	0.791	0.864
BI3	I will always try to use same-day delivery apps in my daily life.	19.14	14.009	0.778	0.745	0.869
BI4	I intend to continue using same-day delivery apps rather than using any alternative means.	19.32	14.281	0.758	0.696	0.873
BI5	I will recommend the use of same-day delivery apps to others.	18.84	15.973	0.719	0.601	0.882
BI6	I intend to use same-day delivery apps more frequently going forward.	19.14	14.342	0.784	0.757	0.869

ANNEXURE F: MOST USED SAME-DAY DELIVERY APPS BASED ON THE DEMOGRAPHIC PROFILE OF RESPONDENTS

		Gender			Generational cohort (age)				
		Female	**Male**	**Total**	**2001 – 2003**	**1990 – 2000**	**1970 – 1989**	**1950 – 1969**	**Total**
Bottles Alcohol Delivery	Not selected	86.6%	77.9%	**84.0%**	80.8%	80.6%	88.1%	94.7%	**83.9%**
	Selected	13.4%	22.1%	**16.0%**	19.2%	19.4%	11.9%	5.3%	**16.1%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Burger King	Not selected	73.6%	69.0%	**72.2%**	73.1%	69.2%	75.1%	89.5%	**72.4%**
	Selected	26.4%	31.0%	**27.8%**	26.9%	30.8%	24.9%	10.5%	**27.6%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
CartRun	Not selected	97.9%	98.6%	**98.1%**	100.0%	97.3%	98.9%	100.0%	**98.1%**
	Selected	2.1%	1.4%	**1.9%**		2.7%	1.1%		**1.9%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Checkers Sixty60	Not selected	57.9%	62.1%	**59.1%**	69.2%	60.8%	54.2%	68.4%	**59.2%**
	Selected	42.1%	37.9%	**40.9%**	30.8%	39.2%	45.8%	31.6%	**40.8%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Debonairs Pizza	Not selected	31.2%	33.1%	**31.7%**	26.9%	31.6%	31.1%	52.6%	**32.0%**
	Selected	68.8%	66.9%	**68.3%**	73.1%	68.4%	68.9%	47.4%	**68.0%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Deliveroo	Not selected	98.5%	97.2%	**98.1%**	100.0%	97.3%	98.9%	100.0%	**98.1%**
	Selected	1.5%	2.8%	**1.9%**		2.7%	1.1%		**1.9%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Dis-Chem DeliverD	Not selected	74.5%	81.4%	**76.6%**	84.6%	76.4%	75.7%	68.4%	**76.3%**
	Selected	25.5%	18.6%	**23.4%**	15.4%	23.6%	24.3%	31.6%	**23.7%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Fishaways	Not selected	86.4%	81.4%	**84.9%**	84.6%	85.6%	83.1%	89.5%	**84.7%**
	Selected	13.6%	18.6%	**15.1%**	15.4%	14.4%	16.9%	10.5%	**15.3%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
iStore (same-day delivery option only)	Not selected	98.2%	93.1%	**96.7%**	96.2%	95.8%	97.7%	100.0%	**96.7%**
	Selected	1.8%	6.9%	**3.3%**	3.8%	4.2%	2.3%		**3.3%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
KFC Delivery	Not selected	49.9%	45.5%	**48.5%**	38.5%	44.9%	53.7%	68.4%	**48.7%**
	Selected	50.1%	54.5%	**51.5%**	61.5%	55.1%	46.3%	31.6%	**51.3%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Krispy Kreme	Not selected	96.7%	95.2%	**96.3%**	88.5%	95.8%	97.7%	100.0%	**96.3%**
	Selected	3.3%	4.8%	**3.7%**	11.5%	4.2%	2.3%		**3.7%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
McDelivery (McDonald's)	Not selected	66.2%	66.9%	**66.4%**	46.2%	63.5%	71.8%	89.5%	**66.6%**
	Selected	33.8%	33.1%	**33.6%**	53.8%	36.5%	28.2%	10.5%	**33.4%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Mr D Food	Not selected	38.0%	38.6%	**38.2%**	19.2%	35.4%	42.9%	57.9%	**38.1%**
	Selected	62.0%	61.4%	**61.8%**	80.8%	64.6%	57.1%	42.1%	**61.9%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Nando's	Not selected	79.2%	75.9%	**78.2%**	80.8%	78.7%	77.4%	78.9%	**78.4%**
	Selected	20.8%	24.1%	**21.8%**	19.2%	21.3%	22.6%	21.1%	**21.6%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Ocean Basket	Not selected	92.3%	91.0%	**91.9%**	92.3%	91.3%	93.8%	84.2%	**92.0%**
	Selected	7.7%	9.0%	**8.1%**	7.7%	8.7%	6.2%	15.8%	**8.0%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
OneCart	Not selected	97.3%	97.2%	**97.3%**	96.2%	98.9%	95.5%	94.7%	**97.3%**
	Selected	2.7%	2.8%	**2.7%**	3.8%	1.1%	4.5%	5.3%	**2.7%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
OrderIn	Not selected	97.0%	98.6%	**97.5%**	96.2%	97.7%	97.2%	100.0%	**97.5%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
	Selected	3.0%	1.4%	**2.5%**	3.8%	2.3%	2.8%		**2.5%**
	Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**
Pekkish SA	Not selected	98.8%	99.3%	**99%**	100%	98.1%	100%	100%	**99%**
	Selected	1.2%	0.7%	**1%**		1.9%			**1%**
	Total	**100%**	**100%**	**100%**	**100.0%**	**100%**	**100%**	**100%**	**100%**
Pick n Pay ASAP!	Not selected	81%	77.2%	**79.9%**	76.9%	79.8%	80.2%	84.2%	**80%**
	Selected	19%	22.8%	**20.1%**	23.1%	20.2%	19.8%	15.8%	**20%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Pizza Hut	Not selected	90.8%	89.7%	**90.5%**	84.6%	89.4%	94.4%	78.9%	**90.5%**
	Selected	9.2%	10.3%	**9.5%**	15.4%	10.6%	5.6%	21.1%	**9.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Quench	Not selected	99.1%	99.3%	**99.2%**	100%	99.6%	98.3%	100%	**99.2%**
	Selected	0.9%	0.7%	**0.8%**		0.4%	1.7%		**0.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Simply Asia	Not selected	97.9%	97.9%	**97.9%**	96.2%	97.7%	99.4%	89.5%	**97.9%**
	Selected	2.1%	2.1%	**2.1%**	3.8%	2.3%	0.6%	10.5%	**2.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Steers	Not selected	74.8%	71%	**73.7%**	57.7%	74.1%	76.3%	68.4%	**73.8%**
	Selected	25.2%	29%	**26.3%**	42.3%	25.9%	23.7%	31.6%	**26.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Stulo	Not selected	99.4%	98.6%	**99.2%**	100%	98.5%	100%	100%	**99.2%**
	Selected	0.6%	1.4%	**0.8%**		1.5%			**0.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Takealot.com (same-day delivery option only)	Not selected	57.6%	53.8%	**56.4%**	53.8%	57.4%	57.1%	47.4%	**56.7%**
	Selected	42.4%	46.2%	**43.6%**	46.2%	42.6%	42.9%	52.6%	**43.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Gender			Generational cohort (age)				
		Female	**Male**	**Total**	**2001 – 2003**	**1990 – 2000**	**1970 – 1989**	**1950 – 1969**	**Total**
The Dog Food App	Not selected	98.5%	93.8%	**97.1%**	100%	96.6%	97.7%	94.7%	**97.1%**
	Selected	1.5%	6.2%	**2.9%**		3.4%	2.3%	5.3%	**2.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Thirst Busters	Not selected	99.7%	96.6%	**98.8%**	100%	98.1%	99.4%	100%	**98.8%**
	Selected	0.3%	3.4%	**1.2%**		1.9%	0.6%		**1.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Uber Eats	Not selected	39.8%	38.6%	**39.4%**	30.8%	36.5%	42.9%	57.9%	**39.4%**
	Selected	60.2%	61.4%	**60.6%**	69.2%	63.5%	57.1%	42.1%	**60.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Woolies Dash	Not selected	88.4%	90.3%	**89%**	96.2%	88.2%	89.3%	89.5%	**89.1%**
	Selected	11.6%	9.7%	**11%**	3.8%	11.8%	10.7%	10.5%	**10.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Zomato	Not selected	99.7%	98.6%	**99.4%**	100%	98.9%	100%	100%	**99.4%**
	Selected	0.3%	1.4%	**0.6%**		1.1%			**0.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Zulzi	Not selected	96.4%	97.2%	**96.7%**	92.3%	96.2%	97.7%	100%	**96.7%**
	Selected	3.6%	2.8%	**3.3%**	7.7%	3.8%	2.3%		**3.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Other	Not selected	98.8%	96.6%	**98.1%**	100%	98.1%	97.7%	100%	**98.1%**
	Selected	1.2%	3.4%	**1.9%**		1.9%	2.3%		**1.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Residing province				Ethnic orientation				
		Gauteng	KwaZulu-Natal	Western Cape	Total	Black	Coloured	Indian	White	Total
Bottles Alcohol Delivery	Not selected	84.9%	88.7%	74.7%	**83.9%**	82.8%	78.6%	100%	89.8%	**84%**
	Selected	15.1%	11.3%	25.3%	**16.1%**	17.2%	21.4%		10.2%	**16%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Burger King	Not selected	71.8%	78.3%	66.7%	**72.3%**	73.3%	64.3%	95.5%	64.4%	**72.1%**
	Selected	28.2%	21.7%	33.3%	**27.7%**	26.7%	35.7%	4.5%	35.6%	**27.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
CartRun	Not selected	97.9%	98.1%	98.9%	**98.1%**	98%	100%	100%	96.6%	**98.1%**
	Selected	2.1%	1.9%	1.1%	**1.9%**	2%			3.4%	**1.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Checkers Sixty60	Not selected	63.2%	55.7%	50.6%	**59.3%**	64.5%	51.8%	40.9%	44.1%	**59.5%**
	Selected	36.8%	44.3%	49.4%	**40.7%**	35.5%	48.2%	59.1%	55.9%	**40.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Debonairs Pizza	Not selected	32%	27.4%	36.8%	**31.8%**	28.8%	33.9%	31.8%	47.5%	**31.8%**
	Selected	68%	72.6%	63.2%	**68.2%**	71.2%	66.1%	68.2%	52.5%	**68.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Deliveroo	Not selected	97.9%	97.2%	100%	**98.1%**	98.3%	98.2%	100%	96.6%	**98.1%**
	Selected	2.1%	2.8%		**1.9%**	1.7%	1.8%		3.4%	**1.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Dis-Chem DeliverD	Not selected	77.3%	76.4%	72.4%	**76.2%**	78.8%	66.1%	77.3%	69.5%	**76.1%**
	Selected	22.7%	23.6%	27.6%	**23.8%**	21.2%	33.9%	22.7%	30.5%	**23.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Fishaways	Not selected	82.8%	88.7%	86.2%	**84.7%**	84%	91.1%	81.8%	83.1%	**84.6%**
	Selected	17.2%	11.3%	13.8%	**15.3%**	16%	8.9%	18.2%	16.9%	**15.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
iStore (same-day delivery option only)	Not selected	96.2%	98.1%	96.6%	**96.7%**	96.5%	94.6%	100%	98.3%	**96.7%**
	Selected	3.8%	1.9%	3.4%	**3.3%**	3.5%	5.4%		1.7%	**3.3%**

		Residing province				Ethnic orientation				
		Gauteng	KwaZulu-Natal	Western Cape	Total	Black	Coloured	Indian	White	Total
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
KFC Delivery	Not selected	49.1%	43.4%	52.9%	**48.6%**	45.6%	48.2%	54.5%	62.7%	**48.4%**
	Selected	50.9%	56.6%	47.1%	**51.4%**	54.4%	51.8%	45.5%	37.3%	**51.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Krispy Kreme	Not selected	95.9%	96.2%	97.7%	**96.3%**	96.2%	98.2%	95.5%	94.9%	**96.3%**
	Selected	4.1%	3.8%	2.3%	**3.7%**	3.8%	1.8%	4.5%	5.1%	**3.7%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
McDelivery (McDonald's)	Not selected	65.3%	69.8%	66.7%	**66.5%**	64.2%	71.4%	77.3%	69.5%	**66.3%**
	Selected	34.7%	30.2%	33.3%	**33.5%**	35.8%	28.6%	22.7%	30.5%	**33.7%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Mr D Food	Not selected	35.1%	41.5%	44.8%	**38.2%**	35.2%	44.6%	50%	45.8%	**38.3%**
	Selected	64.9%	58.5%	55.2%	**61.8%**	64.8%	55.4%	50%	54.2%	**61.7%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Nando's	Not selected	77.7%	74.5%	85.1%	**78.3%**	78.2%	80.4%	63.6%	81.4%	**78.2%**
	Selected	22.3%	25.5%	14.9%	**21.7%**	21.8%	19.6%	36.4%	18.6%	**21.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Ocean Basket	Not selected	92.4%	94.3%	87.4%	**91.9%**	93%	83.9%	100%	89.8%	**91.9%**
	Selected	7.6%	5.7%	12.6%	**8.1%**	7%	16.1%		10.2%	**8.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
OneCart	Not selected	96.9%	97.2%	98.9%	**97.3%**	97.4%	100%	100%	94.9%	**97.5%**
	Selected	3.1%	2.8%	1.1%	**2.7%**	2.6%			5.1%	**2.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
OrderIn	Not selected	97.6%	100%	94.3%	**97.5%**	97.1%	96.4%	100%	100%	**97.5%**
	Selected	2.4%		5.7%	**2.5%**	2.9%	3.6%			**2.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Pekkish SA	Not selected	99%	99.1%	98.9%	**99%**	98.8%	98.2%	100%	100%	**99%**

		Residing province				Ethnic orientation				
		Gauteng	KwaZulu-Natal	Western Cape	Total	Black	Coloured	Indian	White	Total
	Selected	1%	0.9%	1.1%	**1%**	1.2%	1.8%			**1%**
	Total	100%	100%	100%	**100%**	100%	100%	100%	100%	**100%**
Pick n Pay ASAP!	Not selected	79.4%	85.8%	74.7%	**80%**	80.2%	76.8%	90.9%	76.3%	**79.8%**
	Selected	20.6%	14.2%	25.3%	**20%**	19.8%	23.2%	9.1%	23.7%	**20.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Pizza Hut	Not selected	88.7%	93.4%	93.1%	**90.5%**	89.2%	94.6%	95.5%	91.5%	**90.4%**
	Selected	11.3%	6.6%	6.9%	**9.5%**	10.8%	5.4%	4.5%	8.5%	**9.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Quench	Not selected	99%	99.1%	100%	**99.2%**	99.1%	100%	95.5%	100%	**99.2%**
	Selected	1%	0.9%		**0.8%**	0.9%		4.5%		**0.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Simply Asia	Not selected	98.3%	99.1%	95.4%	**97.9%**	98.3%	96.4%	95.5%	98.3%	**97.9%**
	Selected	1.7%	0.9%	4.6%	**2.1%**	1.7%	3.6%	4.5%	1.7%	**2.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Steers	Not selected	73.5%	75.5%	72.4%	**73.8%**	73%	78.6%	86.4%	67.8%	**73.6%**
	Selected	26.5%	24.5%	27.6%	**26.2%**	27%	21.4%	13.6%	32.2%	**26.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Stulo	Not selected	99%	99.1%	100%	**99.2%**	99.1%	98.2%	100%	100%	**99.2%**
	Selected	1%	0.9%		**0.8%**	0.9%	1.8%			**0.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Takealot.com (same-day delivery option only)	Not selected	51.2%	74.5%	52.9%	**56.6%**	57.3%	60.7%	68.2%	45.8%	**56.8%**
	Selected	48.8%	25.5%	47.1%	**43.4%**	42.7%	39.3%	31.8%	54.2%	**43.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
The Dog Food App	Not selected	96.6%	98.1%	97.7%	**97.1%**	96.5%	100%	95.5%	98.3%	**97.1%**
	Selected	3.4%	1.9%	2.3%	**2.9%**	3.5%		4.5%	1.7%	**2.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Residing province				Ethnic orientation				
		Gauteng	KwaZulu-Natal	Western Cape	Total	Black	Coloured	Indian	White	Total
Thirst Busters	Not selected	98.6%	98.1%	100%	**98.8%**	98.5%	100%	100%	98.3%	**98.8%**
	Selected	1.4%	1.9%		**1.2%**	1.5%			1.7%	**1.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Uber Eats	Not selected	35.1%	42.5%	49.4%	**39.3%**	32.0%	51.8%	59.1%	61%	**39.1%**
	Selected	64.9%	57.5%	50.6%	**60.7%**	68.0%	48.2%	40.9%	39%	**60.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Woolies Dash	Not selected	87.6%	87.7%	95.4%	**89%**	88.1%	92.9%	86.4%	91.5%	**89%**
	Selected	12.4%	12.3%	4.6%	**11%**	11.9%	7.1%	13.6%	8.5%	**11%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Zomato	Not selected	99.3%	99.1%	100%	**99.4%**	99.1%	100%	100%	100%	**99.4%**
	Selected	0.7%	0.9%		**0.6%**	0.9%				**0.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Zulzi	Not selected	96.9%	96.2%	96.6%	**96.7%**	95.9%	98.2%	100%	98.3%	**96.7%**
	Selected	3.1%	3.8%	3.4%	**3.3%**	4.1%	1.8%		1.7%	**3.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Other	Not selected	98.3%	98.1%	97.7%	**98.1%**	98.3%	94.6%	100%	100%	**98.1%**
	Selected	1.7%	1.9%	2.3%	**1.9%**	1.7%	5.4%			**1.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

ANNEXURE G: REASONS FOR USING SAME-DAY DELIVERY APPS ACCORDING TO PARTICIPANTS' DEMOGRAPHIC BACKGROUND

		Gender			Generational cohort (age)				
		Female	**Male**	**Total**	**2001 – 2003**	**1990 – 2000**	**1970 – 1989**	**1950 – 1969**	**Total**
… to purchase products.	Never	1.2%	0.7%	**1%**		0.8%	1.1%	5.3%	**1%**
	Rarely	3.6%	3.4%	**3.5%**		3.4%	4.5%		**3.5%**
	Occasionally	32.3%	30.3%	**31.7%**	7.7%	30%	36.7%	36.8%	**31.5%**
	Frequently	41.5%	38.6%	**40.7%**	50%	38%	42.9%	42.1%	**40.6%**
	Always	21.4%	26.9%	**23.0%**	42.3%	27.8%	14.7%	15.8%	**23.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to acquire services.	Never	4.5%	6.2%	**5%**	3.8%	4.6%	5.1%	15.8%	**5.2%**
	Rarely	14.8%	12.4%	**14.1%**	15.4%	14.4%	13.6%	10.5%	**14%**
	Occasionally	33.8%	29%	**32.4%**	23.1%	33.1%	33.3%	26.3%	**32.4%**
	Frequently	32%	35.9%	**33.2%**	38.5%	31.6%	35%	26.3%	**33%**
	Always	14.8%	16.6%	**15.4%**	19.2%	16.3%	13%	21.1%	**15.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to browse for specials, deals or discounts.	Never	1.8%	4.1%	**2.5%**		3.4%	1.7%		**2.5%**
	Rarely	5%	4.1%	**4.8%**		4.9%	4%	15.8%	**4.7%**
	Occasionally	14.8%	13.8%	**14.5%**	23.1%	12.9%	16.9%	5.3%	**14.6%**
	Frequently	38.3%	36.6%	**37.8%**	38.5%	35%	38.4%	63.2%	**37.5%**
	Always	40.1%	41.4%	**40.5%**	38.5%	43.7%	39%	15.8%	**40.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**1%**	**100%**	**100%**
… to collect or use coupons or vouchers.	Never	6.5%	3.4%	**5.6%**		5.3%	6.2%	10.5%	**5.6%**
	Rarely	14.8%	15.9%	**15.1%**	7.7%	16.3%	13.6%	21.1%	**15.1%**
	Occasionally	27.3%	24.1%	**26.3%**	26.9%	21.3%	33.9%	26.3%	**26.4%**
	Frequently	27.6%	27.6%	**27.6%**	30.8%	27.8%	27.7%	21.1%	**27.6%**
	Always	23.7%	29%	**25.3%**	34.6%	29.3%	18.6%	21.1%	**25.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
… to benefit from online-only deals or specials.	Never	2.1%	1.4%	**1.9%**		1.5%	2.3%	5.3%	**1.9%**
	Rarely	7.4%	6.9%	**7.3%**		8%	7.3%	5.3%	**7.2%**
	Occasionally	23.1%	26.2%	**24.1%**	26.9%	22.1%	26.6%	21.1%	**23.9%**
	Frequently	32%	31%	**31.7%**	34.6%	30.8%	32.8%	36.8%	**32%**
	Always	35.3%	34.5%	**35.1%**	38.5%	37.6%	31.1%	31.6%	**35.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare prices.	Never	4.7%	3.4%	**4.4%**		4.6%	5.1%		**4.3%**
	Rarely	9.2%	8.3%	**8.9%**	7.7%	8.7%	9%	10.5%	**8.9%**
	Occasionally	19.3%	17.9%	**18.9%**	23.1%	19%	19.2%	15.8%	**19.2%**
	Frequently	29.1%	33.1%	**30.3%**	38.5%	29.3%	28.2%	52.6%	**30.3%**
	Always	37.7%	37.2%	**37.6%**	30.8%	38.4%	38.4%	21.1%	**37.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare products.	Never	5.3%	4.1%	**5%**	7.7%	5.3%	5.1%		**5.2%**
	Rarely	9.8%	4.8%	**8.3%**	3.8%	8.7%	7.9%	10.5%	**8.2%**
	Occasionally	22.6%	22.1%	**22.4%**	30.8%	19.4%	24.9%	26.3%	**22.3%**
	Frequently	28.8%	26.2%	**28%**	23.1%	29.7%	24.9%	42.1%	**28%**
	Always	33.5%	42.8%	**36.3%**	34.6%	36.9%	37.3%	21.1%	**36.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare services.	Never	5.9%	6.2%	**6%**	3.8%	5.7%	6.8%	5.3%	**6%**
	Rarely	14.5%	9%	**12.9%**	15.4%	12.9%	11.9%	15.8%	**12.8%**
	Occasionally	25.8%	23.4%	**25.1%**	19.2%	24%	27.7%	26.3%	**25.2%**
	Frequently	23.7%	24.1%	**23.9%**	23.1%	25.5%	20.9%	31.6%	**23.9%**
	Always	30.0%	37.2%	**32.2%**	38.5%	31.9%	32.8%	21.1%	**32.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
…to check product availability.	Never	3.3%	0.7%	**2.5%**	3.8%	1.9%	2.8%	5.3%	**2.5%**
	Rarely	6.5%	5.5%	**6.2%**		8%	5.1%		**6.2%**
	Occasionally	18.7%	20.7%	**19.3%**	26.9%	19.8%	16.9%	21.1%	**19.2%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
	Frequently	35.9%	26.9%	**33.2%**	23.1%	32.7%	33.9%	42.1%	**33.0%**
	Always	35.6%	46.2%	**38.8%**	46.2%	37.6%	41.2%	31.6%	**39.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to share product details with others (such as peers, friends or family members).	Never	8.3%	4.8%	**7.3%**	3.8%	5.3%	7.9%	31.6%	**7.2%**
	Rarely	13.1%	17.9%	**14.5%**	15.4%	13.3%	16.4%	10.5%	**14.4%**
	Occasionally	25.8%	22.1%	**24.7%**	26.9%	27.8%	19.8%	21.1%	**24.5%**
	Frequently	26.1%	24.1%	**25.5%**	23.1%	25.1%	28.8%	15.8%	**26%**
	Always	26.7%	31%	**28%**	30.8%	28.5%	27.1%	21.1%	**27.8%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to find the contact details of a specific retailer.	Never	8.3%	5.5%	**7.5%**	7.7%	6.5%	9%	5.3%	**7.4%**
	Rarely	13.1%	20%	**15.1%**	23.1%	18.3%	10.2%	10.5%	**15.3%**
	Occasionally	29.4%	20%	**26.6%**	23.1%	24.3%	28.2%	42.1%	**26.4%**
	Frequently	23.4%	28.3%	**24.9%**	30.8%	24%	26%	21.1%	**24.9%**
	Always	25.8%	26.2%	**25.9%**	15.4%	27%	26.6%	21.1%	**26.0%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to give reviews.	Never	9.2%	7.6%	**8.7%**	7.7%	8.7%	9.6%	5.3%	**8.9%**
	Rarely	21.1%	21.4%	**21.2%**	19.2%	21.3%	20.3%	26.3%	**21%**
	Occasionally	28.2%	26.9%	**27.8%**	34.6%	24.3%	31.1%	31.6%	**27.6%**
	Frequently	21.4%	20%	**21.0%**	23.1%	20.9%	20.3%	26.3%	**21%**
	Always	20.2%	24.1%	**21.4%**	15.4%	24.7%	18.6%	10.5%	**21.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to read reviews.	Never	7.7%	9.7%	**8.3%**	15.4%	8%	7.9%	10.5%	**8.5%**
	Rarely	12.5%	17.2%	**13.9%**	11.5%	13.7%	14.1%	15.8%	**13.8%**
	Occasionally	23.4%	20%	**22.4%**	26.9%	19.8%	25.4%	21.1%	**22.3%**
	Frequently	28.5%	22.8%	**26.8%**	26.9%	25.9%	27.1%	36.8%	**26.8%**
	Always	27.9%	30.3%	**28.6%**	19.2%	32.7%	25.4%	15.8%	**28.7%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
… to find a store closest to you.	Never	2.4%	2.8%	**2.5%**	3.8%	2.3%	2.3%	5.3%	**2.5%**
	Rarely	6.2%	6.9%	**6.4%**	3.8%	5.7%	7.3%	10.5%	**6.4%**
	Occasionally	22%	22.1%	**22%**	19.2%	23.2%	22%	5.3%	**21.9%**
	Frequently	31.5%	26.9%	**30.1%**	38.5%	29.7%	29.9%	26.3%	**30.1%**
	Always	38%	41.4%	**39%**	34.6%	39.2%	38.4%	52.6%	**39.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to avoid having to physically go to a store.	Never	0.9%	1.4%	**1%**		0.8%	1.1%	5.3%	**1%**
	Rarely	4.5%	4.1%	**4.4%**	3.8%	4.9%	2.8%	10.5%	**4.3%**
	Occasionally	23.1%	26.9%	**24.3%**	23.1%	25.1%	22.6%	26.3%	**24.1%**
	Frequently	31.8%	27.6%	**30.5%**	38.5%	27%	35.6%	21.1%	**30.5%**
	Always	39.8%	40%	**39.8%**	34.6%	42.2%	37.9%	36.8%	**40.0%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to maintain social distancing because of the COVID-19 pandemic.	Never	1.5%	2.8%	**1.9%**		1.9%	2.3%		**1.9%**
	Rarely	3.3%	5.5%	**3.9%**		6.1%	1.7%		**3.9%**
	Occasionally	17.8%	15.2%	**17%**	15.4%	17.9%	16.4%	10.5%	**16.9%**
	Frequently	28.8%	31.7%	**29.7%**	26.9%	26.6%	35.6%	21.1%	**29.7%**
	Always	48.7%	44.8%	**47.5%**	57.7%	47.5%	44.1%	68.4%	**47.6%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… because it is convenient to have products delivered to my door.	Never	0.3%	0.7%	**0.4%**		0.4%	0.6%		**0.4%**
	Rarely	3%	1.4%	**2.5%**		3%	1.7%	5.3%	**2.5%**
	Occasionally	15.4%	21.4%	**17.2%**	19.2%	17.9%	15.3%	21.1%	**17.1%**
	Frequently	27%	26.2%	**26.8%**	11.5%	24.7%	31.6%	31.6%	**26.8%**
	Always	54.3%	50.3%	**53.1%**	69.2%	54%	50.8%	42.1%	**53.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… because it is safer than having to physically go to the store.	Never	0.3%	3.4%	**1.2%**	3.8%	0.8%	1.7%		**1.2%**
	Rarely	4.5%	4.8%	**4.6%**	7.7%	4.9%	4%		**4.5%**
	Occasionally	19.6%	14.5%	**18.0%**		20.2%	15.8%	31.6%	**17.9%**
	Frequently	24.6%	25.5%	**24.9%**	23.1%	22.4%	28.8%	26.3%	**24.9%**

		Gender			Generational cohort (age)				
		Female	Male	Total	2001 – 2003	1990 – 2000	1970 – 1989	1950 – 1969	Total
	Always	51%	51.7%	**51.2%**	65.4%	51.7%	49.7%	42.1%	**51.3%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Ethnic orientation					Residing province			
		Black	Coloured	Indian	White	Total	Gauteng	KwaZulu-Natal	Western Cape	Total
… to purchase products.	Never	1.5%				**1%**	1%	1.9%		**1.0%**
	Rarely	2.9%	8.9%	4.5%	1.7%	**3.5%**	3.4%	2.8%	4.6%	**3.5%**
	Occasionally	27.9%	42.9%	45.5%	39%	**31.8%**	30.9%	29.2%	36.8%	**31.6%**
	Frequently	43.3%	32.1%	40.9%	33.9%	**40.7%**	42.3%	42.5%	33.3%	**40.7%**
	Always	24.4%	16.1%	9.1%	25.4%	**22.9%**	22.3%	23.6%	25.3%	**23.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to acquire services.	Never	4.4%	5.4%	13.6%	5.1%	**5%**	4.1%	6.6%	5.7%	**5.0%**
	Rarely	13.4%	12.5%	13.6%	18.6%	**13.9%**	14.8%	12.3%	13.8%	**14%**
	Occasionally	31.1%	41.1%	36.4%	30.5%	**32.4%**	33%	27.4%	36.8%	**32.4%**
	Frequently	34.6%	28.6%	27.3%	30.5%	**33.1%**	30.9%	36.8%	35.6%	**33.1%**
	Always	16.6%	12.5%	9.1%	15.3%	**15.6%**	17.2%	17%	8%	**15.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to browse for specials, deals or discounts.	Never	3.2%				**2.3%**	2.4%	4.7%		**2.5%**
	Rarely	3.2%	7.1%	9.1%	10.2%	**4.8%**	5.2%	1.9%	6.9%	**4.8%**
	Occasionally	14.5%	12.5%	9.1%	20.3%	**14.8%**	15.1%	15.1%	12.6%	**14.7%**
	Frequently	36.3%	48.2%	54.5%	30.5%	**37.8%**	36.4%	38.7%	40.2%	**37.6%**
	Always	42.7%	32.1%	27.3%	39%	**40.3%**	40.9%	39.6%	40.2%	**40.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to collect or use coupons or vouchers.	Never	5.5%	5.4%	4.5%	5.1%	**5.4%**	6.2%	5.7%	3.4%	**5.6%**
	Rarely	14.8%	17.9%	27.3%	10.2%	**15.2%**	15.1%	13.2%	17.2%	**15.1%**
	Occasionally	26.5%	23.2%	36.4%	27.1%	**26.6%**	26.5%	27.4%	25.3%	**26.4%**

		Ethnic orientation					Residing province			
		Black	**Coloured**	**Indian**	**White**	**Total**	**Gauteng**	**KwaZulu-Natal**	**Western Cape**	**Total**
	Frequently	26.7%	33.9%	18.2%	32.2%	**27.9%**	25.8%	27.4%	34.5%	**27.7%**
	Always	26.5%	19.6%	13.6%	25.4%	**24.9%**	26.5%	26.4%	19.5%	**25.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to benefit from online-only deals or specials.	Never	1.7%		4.5%	3.4%	**1.9%**	1.7%	1.9%	2.3%	**1.9%**
	Rarely	7.8%	3.6%	4.5%	8.5%	**7.3%**	7.9%	8.5%	3.4%	**7.2%**
	Occasionally	22.4%	30.4%	22.7%	27.1%	**23.9%**	23.4%	17%	34.5%	**24%**
	Frequently	32%	32.1%	40.9%	30.5%	**32.2%**	31.3%	37.7%	27.6%	**32%**
	Always	36%	33.9%	27.3%	30.5%	**34.7%**	35.7%	34.9%	32.2%	**34.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare prices.	Never	4.1%	3.6%	9.1%	3.4%	**4.2%**	3.8%	6.6%	3.4%	**4.3%**
	Rarely	10.2%	5.4%	4.5%	6.8%	**8.9%**	10%	11.3%	2.3%	**8.9%**
	Occasionally	16.6%	23.2%	31.8%	23.7%	**18.9%**	19.2%	12.3%	26.4%	**19.0%**
	Frequently	29.4%	32.1%	27.3%	35.6%	**30.4%**	29.2%	34%	29.9%	**30.4%**
	Always	39.8%	35.7%	27.3%	30.5%	**37.6%**	37.8%	35.8%	37.9%	**37.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare products.	Never	4.7%	3.6%	9.1%	5.1%	**4.8%**	4.5%	5.7%	5.7%	**5%**
	Rarely	8.4%	8.9%	9.1%	6.8%	**8.3%**	7.6%	13.2%	4.6%	**8.3%**
	Occasionally	19.8%	26.8%	31.8%	28.8%	**22.2%**	22.7%	18.9%	25.3%	**22.3%**
	Frequently	27%	32.1%	27.3%	32.2%	**28.3%**	25.1%	31.1%	34.5%	**28.1%**
	Always	40.1%	28.6%	22.7%	27.1%	**36.4%**	40.2%	31.1%	29.9%	**36.4%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to compare services.	Never	5.8%	3.6%	13.6%	6.8%	**6.0%**	4.1%	9.4%	8.0%	**6%**
	Rarely	11.6%	17.9%	9.1%	15.3%	**12.7%**	13.1%	9.4%	16.1%	**12.8%**
	Occasionally	22.7%	32.1%	31.8%	27.1%	**24.7%**	25.1%	25.5%	24.1%	**25.0%**
	Frequently	25%	19.6%	18.2%	25.4%	**24.1%**	23%	27.4%	23%	**24%**
	Always	34.9%	26.8%	27.3%	25.4%	**32.4%**	34.7%	28.3%	28.7%	**32.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

		Ethnic orientation					Residing province			
		Black	Coloured	Indian	White	Total	Gauteng	KwaZulu-Natal	Western Cape	Total
…to check product availability.	Never	2.3%	3.6%		3.4%	**2.5%**	1.7%	2.8%	4.6%	**2.5%**
	Rarely	6.4%	3.6%	4.5%	8.5%	**6.2%**	4.8%	9.4%	6.9%	**6.2%**
	Occasionally	17.7%	17.9%	40.9%	16.9%	**18.7%**	19.9%	17.9%	18.4%	**19.2%**
	Frequently	31.4%	37.5%	36.4%	39%	**33.3%**	33%	33%	33.3%	**33.1%**
	Always	42.2%	37.5%	18.2%	32.2%	**39.3%**	40.5%	36.8%	36.8%	**39%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to share product details with others (such as peers, friends or family members).	Never	6.7%	7.1%		13.6%	**7.3%**	7.2%	7.5%	6.9%	**7.2%**
	Rarely	15.1%	5.4%	4.5%	23.7%	**14.6%**	15.1%	13.2%	13.8%	**14.5%**
	Occasionally	22.1%	30.4%	54.5%	20.3%	**24.3%**	23.0%	29.2%	24.1%	**24.6%**
	Frequently	27%	17.9%	27.3%	27.1%	**26%**	25.8%	26.4%	25.3%	**25.8%**
	Always	29.1%	39.3%	13.6%	15.3%	**27.9%**	28.9%	23.6%	29.9%	**27.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to find the contact details of a specific retailer.	Never	7.3%	5.4%	9.1%	10.2%	**7.5%**	8.2%	6.6%	5.7%	**7.4%**
	Rarely	14.2%	12.5%	22.7%	20.3%	**15.2%**	15.8%	10.4%	18.4%	**15.1%**
	Occasionally	23.8%	32.1%	31.8%	32.2%	**26.2%**	24.4%	33%	25.3%	**26.4%**
	Frequently	26.7%	25%	18.2%	16.9%	**24.9%**	25.4%	24.5%	24.1%	**25%**
	Always	27.9%	25%	18.2%	20.3%	**26.2%**	26.1%	25.5%	26.4%	**26%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to give reviews.	Never	7.8%	5.4%	13.6%	13.6%	**8.5%**	9.3%	6.6%	9.2%	**8.7%**
	Rarely	19.5%	21.4%	36.4%	25.4%	**21.2%**	19.2%	21.7%	26.4%	**21.1%**
	Occasionally	26.7%	35.7%	27.3%	25.4%	**27.7%**	27.5%	25.5%	31%	**27.7%**
	Frequently	21.2%	19.6%	18.2%	22%	**21%**	21.3%	24.5%	16.1%	**21.1%**
	Always	24.7%	17.9%	4.5%	13.6%	**21.6%**	22.7%	21.7%	17.2%	**21.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to read reviews.	Never	8.7%	5.4%	4.5%	8.5%	**8.1%**	9.6%	5.7%	6.9%	**8.3%**

		Ethnic orientation					Residing province			
		Black	Coloured	Indian	White	Total	Gauteng	KwaZulu-Natal	Western Cape	Total
	Rarely	12.8%	12.5%	18.2%	20.3%	**13.9%**	12.7%	13.2%	18.4%	**13.8%**
	Occasionally	18.6%	25%	50%	32.2%	**22.5%**	23%	21.7%	20.7%	**22.3%**
	Frequently	27.9%	30.4%	9.1%	23.7%	**26.8%**	24.4%	30.2%	31%	**26.9%**
	Always	32%	26.8%	18.2%	15.3%	**28.7%**	30.2%	29.2%	23%	**28.7%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to find a store closest to you.	Never	2%		13.6%	3.4%	**2.5%**	1.4%	5.7%	2.3%	**2.5%**
	Rarely	6.4%	5.4%	4.5%	8.5%	**6.4%**	7.9%	3.8%	4.6%	**6.4%**
	Occasionally	21.5%	21.4%	22.7%	23.7%	**21.8%**	22.7%	22.6%	18.4%	**21.9%**
	Frequently	28.2%	39.3%	31.8%	32.2%	**30.1%**	28.5%	35.8%	28.7%	**30.2%**
	Always	41.9%	33.9%	27.3%	32.2%	**39.1%**	39.5%	32.1%	46.0%	**39.0%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to avoid having to physically go to a store.	Never	0.9%		4.5%	1.7%	**1%**	0.7%	1.9%	1.1%	**1%**
	Rarely	4.1%	5.4%	4.5%	5.1%	**4.4%**	4.1%	5.7%	3.4%	**4.3%**
	Occasionally	21.2%	30.4%	45.5%	25.4%	**23.9%**	23%	30.2%	20.7%	**24.2%**
	Frequently	29.4%	28.6%	31.8%	39%	**30.6%**	30.2%	30.2%	32.2%	**30.6%**
	Always	44.5%	35.7%	13.6%	28.8%	**40.1%**	41.9%	32.1%	42.5%	**39.9%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… to maintain social distancing because of the COVID-19 pandemic.	Never	1.5%	3.6%		3.4%	**1.9%**	1.7%	0.9%	3.4%	**1.9%**
	Rarely	4.1%	3.6%	4.5%	3.4%	**4%**	5.8%	0.9%	1.1%	**3.9%**
	Occasionally	14.8%	19.6%	31.8%	20.3%	**16.8%**	13.1%	25.5%	19.5%	**16.9%**
	Frequently	30.5%	19.6%	27.3%	33.9%	**29.5%**	29.6%	34%	25.3%	**29.8%**
	Always	49.1%	53.6%	36.4%	39%	**47.8%**	49.8%	38.7%	50.6%	**47.5%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… because it is convenient to have products delivered to my door.	Never	0.6%				**0.4%**	0.3%	0.9%		**0.4%**
	Rarely	2.6%	1.8%	4.5%	1.7%	**2.5%**	3.1%	0.9%	2.3%	**2.5%**
	Occasionally	16%	19.6%	13.6%	22.0%	**17%**	14.8%	22.6%	18.4%	**17.1%**
	Frequently	24.7%	21.4%	40.9%	40.7%	**27%**	24.7%	33%	26.4%	**26.9%**

		Ethnic orientation					Residing province			
		Black	**Coloured**	**Indian**	**White**	**Total**	**Gauteng**	**KwaZulu-Natal**	**Western Cape**	**Total**
	Always	56.1%	57.1%	40.9%	35.6%	**53%**	57.0%	42.5%	52.9%	**53.1%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
… because it is safer than having to physically go to the store.	Never	1.2%	1.8%		1.7%	**1.2%**	1%	0.9%	2.3%	**1.2%**
	Rarely	4.9%	3.6%	4.5%	3.4%	**4.6%**	4.1%	5.7%	4.6%	**4.5%**
	Occasionally	15.4%	26.8%	18.2%	23.7%	**17.9%**	15.8%	20.8%	21.8%	**18%**
	Frequently	24.1%	17.9%	31.8%	35.6%	**25.2%**	24.4%	27.4%	24.1%	**25.0%**
	Always	54.4%	50%	45.5%	35.6%	**51.1%**	54.6%	45.3%	47.1%	**51.2%**
	Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**

ANNEXURE H: STANDARDISED REGRESSION WEIGHTS AND CORRELATION ESTIMATES OF THE ORIGINAL MODEL

Standardised regression weights				Correlations			
			Estimate				Estimate
PE1	←	PE	0.67	PE	↔	EE	0.883
PE2	←	PE	0.74	PE	↔	FC	0.946
PE3	←	PE	0.63	PE	↔	SI	0.530
PE4	←	PE	0.74	PE	↔	HM	0.830
PE5	←	PE	0.73	PE	↔	HA	0.847
PE6	←	PE	0.72	PE	↔	PV	-0.823
EE1	←	EE	0.75	PE	↔	LSC	0.935
EE2	←	EE	0.68	PE	↔	PR	-0.214
EE3	←	EE	0.74	PE	↔	PSE	0.847
EE4	←	EE	0.67	PE	↔	ATT	0.980
EE5	←	EE	0.51	PE	↔	BI	0.847
FC1	←	FC	0.27	EE	↔	FC	1.034
FC2	←	FC	0.60	EE	↔	SI	0.408
FC3	←	FC	0.75	EE	↔	HM	0.804
FC4	←	FC	0.69	EE	↔	HA	0.672
FC5	←	FC	0.71	EE	↔	PV	-0.758
SI1	←	SI	0.63	EE	↔	LSC	0.808
SI2	←	SI	0.66	EE	↔	PR	-0.218
SI3	←	SI	0.83	EE	↔	PSE	0.999
SI4	←	SI	0.63	EE	↔	ATT	0.902
SI5	←	SI	0.74	EE	↔	BI	0.730
SI6	←	SI	0.56	FC	↔	SI	0.452
HM1	←	HM	0.78	FC	↔	HM	0.821
HM2	←	HM	0.74	FC	↔	HA	0.709
HM3	←	HM	0.66	FC	↔	PV	-0.803
HM4	←	HM	0.77	FC	↔	LSC	0.870
HM5	←	HM	0.71	FC	↔	PR	-0.206
HA1	←	HA	0.70	FC	↔	PSE	1.006
HA2	←	HA	0.68	FC	↔	ATT	0.969
HA3	←	HA	0.69	FC	↔	BI	0.769
HA4	←	HA	0.75	SI	↔	HM	0.640
PV1	←	PV	-0.74	SI	↔	HA	0.736
PV2	←	PV	-0.74	SI	↔	PV	-0.578
PV3	←	PV	-0.68	SI	↔	LSC	0.664
PV4	←	PV	-0.71	SI	↔	PR	0.251
PV5	←	PV	0.23	SI	↔	PSE	0.292
LSC1	←	LSC	0.74	SI	↔	ATT	0.596
LSC2	←	LSC	0.79	SI	↔	BI	0.563
LSC3	←	LSC	0.72	HM	↔	HA	0.859
LSC4	←	LSC	0.70	HM	↔	PV	-0.826
LSC5	←	LSC	0.56	HM	↔	LSC	0.917

Standardised regression weights				Correlations			
			Estimate				Estimate
LSC6	←	LSC	0.55	HM	↔	PR	-0.096
LSC7	←	LSC	0.63	HM	↔	PSE	0.677
LSC8	←	LSC	0.66	HM	↔	ATT	0.886
LSC9	←	LSC	0.68	HM	↔	BI	0.776
PR1	←	PR	0.75	HA	↔	PV	-0.786
PR2	←	PR	0.56	HA	↔	LSC	0.985
PR3	←	PR	-0.10	HA	↔	PR	0.014
PR4	←	PR	0.71	HA	↔	PSE	0.571
PR5	←	PR	0.83	HA	↔	ATT	0.853
PR6	←	PR	0.70	HA	↔	BI	0.802
PR7	←	PR	0.78	PV	↔	LSC	-0.839
PR8	←	PR	0.65	PV	↔	PR	0.162
PSE1	←	PSE	0.63	PV	↔	PSE	-0.650
PSE2	←	PSE	0.75	PV	↔	ATT	-0.846
PSE3	←	PSE	0.77	PV	↔	BI	-0.741
PSE4	←	PSE	0.75	LSC	↔	PR	-0.081
PSE5	←	PSE	0.79	LSC	↔	PSE	0.735
ATT1	←	ATT	0.70	LSC	↔	ATT	0.979
ATT2	←	ATT	0.69	LSC	↔	BI	0.866
ATT3	←	ATT	0.69	PR	↔	PSE	-0.295
ATT4	←	ATT	0.65	PR	↔	ATT	-0.192
ATT5	←	ATT	0.65	PR	↔	BI	-0.133
ATT6	←	ATT	0.71	PSE	↔	ATT	0.873
BI1	←	BI	0.67	PSE	↔	BI	0.622
B12	←	BI	0.79	ATT	↔	BI	0.835
BI3	←	BI	0.79				
BI4	←	BI	0.75				
BI5	←	BI	0.77				
BI6	←	BI	0.81				

Key: Behavioural intention (BI); Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Performance expectancy (PE); Effort expectancy (EE); Facilitating conditions (FC); Hedonic motivation (HM); Habit (HA); Price value (PV); Lifestyle compatibility (LSC); Attitude towards use (ATT)

ANNEXURE I: SQUARED MULTIPLE CORRELATIONS (R^2), STANDARDISED REGRESSION WEIGHTS AND CORRELATION ESTIMATES FOR THE STRUCTURAL MODEL

Standardised regression weights and correlations for the structural model

Standardised regression weights				Correlations			
			Estimate				Estimate
BI	←	**SI**	**-0.026**	SI	↔	PR	0.130
BI	←	**PR**	**-0.020**	SI	↔	PCV	0.701
BI	←	**PCV**	**0.857**	SI	↔	BI	0.572
BI1	←	BI	0.673	PR	↔	PCV	-0.133
BI2	←	BI	0.789	PR	↔	BI	-0.137
BI3	←	BI	0.785	BI	↔	PCV	0.841
BI4	←	BI	0.737				
BI5	←	BI	0.778				
BI6	←	**BI**	**0.806**				
SI1	←	SI	0.661				
SI2	←	SI	0.698				
SI3	←	**SI**	**0.842**				
PR1	←	PR	0.756				
PR5	←	**PR**	**0.826**				
PR6	←	PR	0.698				
PR7	←	**PR**	**0.797**				
PR8	←	PR	0.636				
PE1	←	PCV	0.664				
PE3	←	PCV	0.648				
EE2	←	PCV	0.605				
EE3	←	PCV	0.638				
FC2	←	PCV	0.645				
HM1	←	PCV	0.688				
HA1	←	PCV	0.671				
HA3	←	PCV	0.653				
PV1	←	PCV	0.657				
PV2	←	PCV	0.652				
PV4	←	PCV	0.644				
LSC4	←	PCV	0.696				
LSC8	←	PCV	0.648				
ATT1	←	PCV	0.720				
ATT2	←	PCV	0.687				
ATT3	←	PCV	0.680				
ATT5	←	PCV	0.661				

Key: Behavioural intention (BI); Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Performance expectancy (PE); Effort expectancy (EE); Facilitating conditions (FC); Hedonic motivation (HM); Habit (HA); Price value (PV); Lifestyle compatibility (LSC); Attitude towards use (ATT)

Squared multiple correlations

	Estimates		Estimates
BI	0.708	PE1	0.441
BI1	0.453	PE3	0.420
BI2	0.623	EE2	0.366
BI3	0.616	EE3	0.407
BI4	0.544	FC2	0.415
BI5	0.606	HM1	0.474
BI6	0.650	HA1	0.450
		HA3	0.426
SI1	0.437	PV1	0.432
SI2	0.487	PV2	0.425
SI3	0.709	PV4	0.415
		LSC4	0.484
PR1	0.571	LSC8	0.420
PR5	0.682	ATT1	0.518
PR6	0.487	ATT2	0.471
PR7	0.635	ATT3	0.462
PR8	0.405	ATT5	0.437

Key: Behavioural intention (BI); Social influence (SI); Perceived risk (PR); Perceived customer value (PCV); Performance expectancy (PE); Effort expectancy (EE); Facilitating conditions (FC); Hedonic motivation (HM); Habit (HA); Price value (PV); Lifestyle compatibility (LSC); Attitude towards use (ATT)

ANNEXURE J: GROUP MEAN DIFFERENCE RESULTS

Gender: Independent *t*-test

Construct	Gender	n	Mean	Std dev.	Std error mean
Social influence	Female	337	3.82	0.836	0.046
	Male	145	3.85	0.778	0.065
Perceived risk	Female	337	3.12	0.938	0.051
	Male	145	3.10	1.045	0.087
Perceived customer value	Female	337	4.18	0.537	0.029
	Male	145	4.21	0.587	0.049
Behavioural intention	Female	337	4.23	0.638	0.035
	Male	145	4.26	0.596	0.049

Gender: Independent sample *t*-test (Levene's test for equality of variances)

		Levene's test for equality of variances		*t*-test for equality of means						
		F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean difference	Std error difference	95% confidence interval of the difference	
									Lower	Upper
Social influence	Equal variances assumed	1.271	0.260	-0.308	480	0.759	-0.025	0.081	-0.185	0.134
	Equal variances not assumed			-0.316	291.723	0.752	-0.025	0.079	-0.181	0.131
Perceived risk	Equal variances assumed	3.868	0.050	0.228	480	0.820	0.022	0.096	-0.168	0.211
	Equal variances not assumed			0.218	248.168	0.828	0.022	0.101	-0.176	0.220
Perceived customer value	Equal variances assumed	0.577	0.448	-0.526	480	0.599	-0.029	0.055	-0.137	0.079
	Equal variances not assumed			-0.508	252.163	0.612	-0.029	0.057	-0.141	0.083
Behavioural intention	Equal variances assumed	2.283	0.131	-0.585	480	0.559	-0.036	0.062	-0.159	0.0858
	Equal variances not assumed			-0.601	290.663	0.548	-0.036	0.061	-0.155	0.083

Note: $p \leq 0.05$

Gender: Independent sample effect sizes

		Standardiser	Point estimate	95% confidence interval	
				Lower	Upper
Social influence	Cohen's d	0.819	-0.031	-0.225	0.164
	Hedges' correction	0.820	-0.030	-0.225	0.164
	Glass's delta	0.778	-0.032	-0.227	0.163
Perceived risk	Cohen's d	0.971	0.023	-0.172	0.217
	Hedges' correction	0.973	0.023	-0.172	0.217
	Glass's delta	1.045	0.021	-0.174	0.216
Perceived customer value	Cohen's d	0.552	-0.052	-0.247	0.142
	Hedges' correction	0.553	-0.052	-0.247	0.142
	Glass's delta	0.587	-0.049	-0.244	0.146
Behavioural intention	Cohen's d	0.626	-0.058	-0.253	0.137
	Hedges' correction	0.627	-0.058	-0.252	0.136
	Glass's delta	0.596	-0.061	-0.256	0.134

Generational cohort: Independent sample *t*-test

Construct	Generational cohort	n	Mean	Std dev.	Std error mean
Social influence	1950-1989	196	3.80	0.865	0.062
	1990-2003	289	3.85	0.783	0.046
Perceived risk	1950-1989	196	2.94	0.954	0.068
	1990-2003	289	3.24	0.962	0.057
Perceived customer value	1950-1989	196	4.19	0.574	0.041
	1990-2003	289	4.18	0.535	0.031
Behavioural intention	1950-1989	196	4.26	0.671	0.048
	1990-2003	289	4.22	0.591	0.035

Generational cohort: Independent sample *t*-test (Levene's test for equality of variances)

		Levene's test for equality of variances		*t*-test for equality of means						
		F	Sig.	*t*	*df*	Sig. (2-tailed)	Mean difference	Std error difference	95% confidence interval of the difference	
									Lower	Upper
Social influence	Equal variances assumed	1.447	0.230	0.686	483	0.493	0.052	0.076	-0.097	0.200
	Equal variances not assumed			0.673	390.269	0.501	0.052	0.077	-0.100	0.203
Perceived risk	Equal variances assumed	0.004	0.948	3.373	483	**<0.001****	0.299	0.089	0.125	0.474
	Equal variances not assumed			3.379	421.243	**<0.001****	0.299	0.089	0.125	0.473
Perceived customer value	Equal variances assumed	3.689	0.055	-0.092	483	0.927	-0.005	0.051	-0.105	0.096
	Equal variances not assumed			-0.090	398.382	0.928	-0.005	0.052	-0.106	0.097
Behavioural intention	Equal variances assumed	4.637	**0.032***	-0.749	483	0.454	-0.043	0.058	-0.157	0.070
	Equal variances not assumed			-0.731	382.515	0.465	-0.043	0.059	-0.160	0.073

Note: *$p \leq 0.05$; ** $p \leq 0.001$

Generational cohort: Independent sample effect sizes

		Standardiser	Point estimate	95% confidence interval	
				Lower	Upper
Social influence	Cohen's d	0.817	0.063	-0.118	0.245
	Hedges' correction	0.818	0.063	-0.118	0.244
	Glass's delta	0.865	0.060	-0.122	0.241
Perceived risk	Cohen's d	0.959	**0.312**	0.130	0.494
	Hedges' correction	0.960	0.312	0.129	0.494
	Glass's delta	0.954	0.314	0.129	0.497
Perceived customer value	Cohen's d	0.551	-0.008	-0.190	0.173
	Hedges' correction	0.552	-0.008	-0.190	0.173
	Glass's delta	0.574	-0.008	-0.189	0.173
Behavioural intention	Cohen's d	0.624	-0.069	-0.251	0.112
	Hedges' correction	0.625	-0.069	-0.250	0.112
	Glass's delta	0.671	-0.065	-0.246	0.117