A Contextualized Model for a Persuasive Technology Mobile Health Self-Monitoring System for Diabetic Patients in South African Communities

By

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I declare that the above thesis is my own work and that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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DEDICATION

This thesis is dedicated to my late parents Mr and Mrs J Kgasi. You always believed in me, and this made me gain encouragement and empowerment. I pray for the good Lord to grant you eternal life.

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First, I would like to thank and give glory to Almighty God, my creator and protector, for being with me throughout this journey.

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ABSTRACT

Self-care for health is essential as a way to reduce the health inequality gap that manifests itself in a variety of ways. These include the lack of access to medical and food resources and other unmet daily needs. In particular, in less privileged communities the lack of alignment between innovative health-related technologies and disease burdens, as well as a lack of adequate service, contribute to inadequate monitoring of chronically ill patients. Chronic diseases cause a high number of deaths and place a considerable strain on the health systems of many countries, especially developing ones. Patients suffering from chronic conditions become traumatised as they live with an incurable ailment, and this negatively affects their adherence to medical regimes, with serious consequences. This study sought to develop a contextualized model for use by the persuasive technology mHealth self-monitoring (mHealthSM) system for patients with diabetes in South African communities. The model informed the architecture of the artifact (the mHealthSM system) intended to be used as a reminder for diabetic patients to take their medicine.

The study followed a positivist paradigm incorporating the quantitative approach and Design Science Research. Data were collected from district hospitals in three provinces of South Africa, namely Gauteng, KwaZulu Natal and Mpumalanga. The model was validated using Smart-PLS and the mHealthSM system artifact was based on this model, and was developed and evaluated. The results indicated that environmental aspects significantly influenced all the strategies used to inform patients about the necessary changes of behaviour for medical adherence. Furthermore, characteristics of the associated technology, such as effort expectancy and performance expectancy, played a significant role in influencing the change of behaviour of patients.

However, social aspects, culture and individual characteristics due to skills were found not to be significant. Furthermore, the artifact evaluation indicated that it is reliable, highly valid and performs as expected. Theoretically, this study contributes to the development of a contextualized model that incorporates the interacting effects of the moderating factors to inform the medical adherence by patients. Furthermore, the study contributes to the management and practice of healthcare personnel, as they would leverage the developed model and artifact developed to inform their monitoring of chronically ill patients. Methodologically, the study combined three aspects namely, an analysis of moderating factors, the combination of the quantitative and Design Science approaches to develop both the model and the artifact, and lastly the validation of the model and the evaluation of the artifact into a single study. This study recommends that future research should work jointly with healthcare personnel to enable the collection of data from patients rather than from healthcare workers only. The study also recommends deployment of the developed mHealthSM to the cloud to increase its stability, scalability and data storage.

Keywords: Diabetes; Chronic diseases; Health care provision; Mobile health; Patients self-monitoring; Medical adherence, Persuasive technology, Remote healthcare provision

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LIST OF ACRONYMS

AVE	Average Variance Explained
COVID-19	Coronavirus Disease of 2019
CR	Composite Reliability
DSR	Design Science Research
GDP	Gross Domestic Product
HTMT	Heterotrait-Monotrait Ratio
IDE	Integrated Development Environment
mHealth	Mobile Health
NCD	Non-Communicable Disease
PDAs	Portable Digital Assistants
PLS	Partial Least Squares
SA	South Africa
SEM	Structural Equation Modelling
SPSS	Statistical Package for Social Scientists
Smart-PLS	Smart Partial Least Squares
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT-2	Extended Model of the Unified Theory of Acceptance and Use of Technology
WHO	World Health Organization

GLOSSARY

Artifact	An artifact is described as a material object made by (human) agents as means to achieve practical ends. In the context of this study, it is a product that has been developed to represent an actual system.
Back end	The back end refers to those parts of a computer application or a program's code that allow it to operate and that cannot be accessed by a user. In systems development this means working on server-side software, which focuses on everything that the user cannot see on a website. The purpose of the back end is to ensure that the website performs correctly, and it focusses on databases, back end logic, application programming interface (APIs), architecture and servers.
Chronic Diseases	These are diseases or health conditions that persist for one or more years and require ongoing medical attention, limit activities of daily living or both. Certain chronic diseases, such as heart disease, cancer and diabetes, are the leading causes of death and disability in both developed and developing countries.
Communicable diseases	Communicable diseases, also known as infectious diseases or transmissible diseases, result from infection, and the presence and growth of pathogenic biologic agents (capable of causing disease) in a human or other animal host. Their common characteristic is that they spread from one person to another, from an animal to a person, or from a surface or a food.
Conceptual Model	A conceptual model is comprised of a set of variables, formulated from one or more theories, suggesting the direction to take to answer research questions. Such a model needs to be validated through data collection and analysis. It is an analytical tool and may have several variations related to different contexts.
Contextualized Model	Contextualization is an endeavour to link theoretical constructs to a real-world context. The contextualized model is developed to link research to the setting or settings in which the study is conducted or the situation within which it exists.
Design Science Research Methodology	Design Science is a research paradigm that focusses on the development and validation of prescriptive knowledge. The main goal of Design Science Research is to develop knowledge that professionals of the discipline in question can use to design solutions to their field problems.

Discriminant validity	Discriminant validity is a subtype of construct validity that is used to show how well a test measures the concept it was designed to measure. Discriminant validity specifically measures whether constructs that theoretically should not be related to each other are, in fact, unrelated.
Front end	Front end development focuses on the visual aspects of a website, application or system. It is the part that users see and interact with.
Heterotrait-Monotrait Ratio	HTMT criterion measures the average correlations of the indicators across constructs. The acceptable levels of discriminant validity is less than 0.90 as suggested by Henseler et al. (2015). It is recommended to identify distinctiveness of the constructs, but it should be used caution if it in the range 0.85 or 0.90.
Mobile Health (mHealth)	The practice of medicine and healthcare over mobile devices, tablets, PDAs and computers.
Moderating /Interacting effects	Moderation, also known as effect modification or interacting effects, occurs when the relationship between two variables depends on a third variable. The third variable is referred to as the moderator variable (or effect modifier) or simply the moderator (or modifier).
Mortality and Morbidity	Morbidity is the state of being unhealthy for a particular disease or situation, whereas mortality is the number of deaths that occur in a population.
Non-communicable diseases	Non-communicable diseases (NCDs) are diseases that are not spread through infection or through other people but are typically caused by unhealthy behaviours. They are also regarded as a group of conditions that are not mainly caused by an acute infection, but result in long-term health consequences and often create a need for long-term treatment and care. These conditions include cancer, cardiovascular disease, diabetes, and chronic lung disease. NCDs are the leading cause of death worldwide and present a great threat to health and development, particularly in low and middle-income countries.
Partial Least Square Structural Equation Modelling (PLS-SEM)	PLS-SEM is an alternative method to the historically more commonly used covariance-based SEM (CB-SEM) when analysing the data using structural equation modelling (SEM).

PUBLICATIONS FROM THE STUDY

a) Kgasi, M., Chimbo, B. & Motsi, L. (2023). mHealth self-monitoring model for medicine adherence of diabetic patients in developing countries: A structural equation modelling approach. JMIR Formative Research, 2023; 7: e49407, https://doi: 10.2196/49407

b) Kgasi, M., Chimbo, B. & Motsi, L. (2024). A persuasive technology mHealth self-monitoring system for intervention in diabetic patients' medical adherence. International Journal of Science Annals.2024; 7:2. https://culturehealth.org/ijsa_archive/ijsa.2024.2.2.pdf

c) Kgasi, M., Chimbo, B., & Motsi, L. (In Progress). mHealth as a tool to manage chronic diseases in developing countries: A case of diabetes

CHAPTER 1: INTRODUCTION

This chapter introduces the field of the study and gives the background from which a problem statement was derived. The chapter presents the research objectives and the questions that the study set to answer. It gives the justification for this study and future similar ones that may be conducted; this is followed by an overview of the contributions made. Finally, the chapter outlines the study, summarizing each chapter of this thesis.

1.1 Introduction to the Field of Study

Non-adherence to medications is one of the predictors of hospitalization, and increases mortality rates and readmissions to the hospital, all of which negatively impact the patient's quality of life. Lack of routine in taking medications can be attributed to the need for constant refills, a sense that the condition had improved, and hence medical treatments were unnecessary, forgetfulness, or unwillingness to take medications, as well as the non-availability of medicine. Psychologically, patients with comorbid illnesses, who frequently take medicine, are likely to avoid adherence due to fatigue and stigmatization. A sufficient effort must be made to improve patients' adherence to their medications and should include increased awareness, support from healthcare workers and relatives, as well as leveraging technological innovations. This study investigated the use of mobile health (mHealth) self-monitoring to improve the adherence to a medication regimen by patients with diabetes.

Chronic diseases, and diseases with long-lasting effects, i.e., those lasting for more than three months, exacerbate other causes of death and disability worldwide. Chronic diseases have a high prevalence and are pervasive across all socio-economic classes in both developing and developed countries (WHO, 2019; Lin, Richardson, Dobrin, Pop-Busui, Piatt, & Piette, 2022). These chronic conditions require medication that must be taken regularly by the patient. In addition to side effects, this routine taking of medicine regularly over a long period, together with the strain of living with conditions that cannot be cured, causes distress and depression. For example, patients who are aware that they are living with an incurable malignancy often suffer from anxiety and depression that makes drug regimen adherence a challenge (Kalema & Mosoma, 2019; Meier, Taubenheim, Lordick, Mehnert-Theuerkauf & Götze, 2020).

South Africa, like many other developing countries, is faced with an escalating burden of both infectious and chronic diseases and this causes increasing threats to the country's health systems and economic growth (Akindele & Useh, 2021; Narsai, Leufkens, & Mantel-Teeuwisse, 2021). According to Achoki et al. (2022), the COVID-19 pandemic worsened the existing challenges, namely the high burden of already prevalent chronic infectious diseases, such as HIV/AIDS and TB, and maternal and child mortality. This is in addition to a long list of non-communicable diseases (NCDs), such as hypertension and cardiovascular diseases, diabetes, cancer, mental illnesses and chronic lung diseases like asthma. Additional health challenges come from injury and trauma which have resulted in a high mortality rate in both youth and adults. Chronic diseases, both communicable and non-communicable, have become prominent, leading to high morbidity and mortality rates worldwide (WHO, 2014; Narsai et al., 2021). The prevalence of communicable and non-communicable diseases has increased over the last two decades and these are now the leading cause of morbidity and mortality in developing countries, especially in Africa and including South Africa (Bradshaw, Nannan, Pillay-van Wyk, Laubscher, Groenewald & Dorrington, 2019; Govuzela, Thsehla, & de Villiers, 2018).

While the South African government spends a lot of money on health, there are still notable inequalities between urban and rural settings that call for a concerted effort to bridge the healthcare gap (Kalema & Mosoma, 2019). This is especially so since the majority of South Africans in rural settings depend on public health provision (Bradshaw et al., 2019). The increasing number of individuals with co- and multi-morbidities indicates an urgent need to improve the monitoring of patients with multiple co-existing diseases. Leveraging technology as a way to empower patients to monitor their own health and encouraging adherence to medical prescriptions and treatment is important, and this is needed throughout a patient's life (Kalema & Mosoma, 2019; Meier et al., 2020).

Meier et al. (2020) observed that, much as patients' empowerment to monitor their health is crucial and is a great achievement, achieving this is hindered by numerous obstacles. These include culture, communication, fear of stigmatization, excessive use of alcohol and drug abuse, as well as lack of education. However, the South African mHealth Strategy 2015-2019 report indicates that most mHealth interventions are based on small projects, and hence are not integrated into mainstream government health services and are not thoroughly evaluated regarding long-term effectiveness. The report emphasizes that, for these projects to be beneficial to the South African health services, they must be contextualized in terms of the South African environment, and study the training of health workers and appropriateness of technology choice (mHealth Strategy, 2019).

Arshed, Mahmud, Minhat, Ying and Umer (2023) note that although many health monitoring systems have been suggested and implemented in developed countries, few have been developed specifically for the context of developing countries bearing in mind the many homogeneous health and technological challenges. Earlier researchers such as Leon and Schneider (2012) and Mahmood, Mckinstry, Luz, Fairhurst, Nasim, Hazir, and RESPIRE Collaboration (2020) note that those mHealth monitoring systems that were inaugurated considering the perspective of developing countries, emphasized monitoring the performance and support of healthcare workers in communities. However, few, if any, focussed on patient empowerment. Similar sentiments were put forward by Akindele and Useh (2021) and Cruz-Ramos, Alor-Hernández, Colombo-Mendoza, Sánchez-Cervantes, Rodrguez-Mazahua and Guarneros-Nolasco (2022), who noted that there is a need to develop health monitoring systems targeting patients.

According to Kumar, Hasan, and Afroz (2023), there is an increasing use of mHealth interventions where text messages are sent on mobile phones to remind patients to follow the prescribed treatment and medicine. However, Van der Pol, Ntinga, Mkhize, and van Heerden (2022) revealed that, although text messages have the potential to improve patient adherence, few studies have shown sufficient evidence to confirm the long-term effect of mHealth interventions. Van der Pol et al. (2022) emphasize a need for the integration of technology together with changes in individual behaviour to achieve effective mHealth self-monitoring. Therefore, more studies are needed to study this.

1.2 Background of the Study

Healthcare provision is largely dependent on the adequacy and competency of the health workforce. This dictates the quality of health services and leads to better health and the well-being of patients. Researchers, such as Bradshaw et al. (2019) and Kalema and Mosoma (2019), remind us that the post-Apartheid era in South Africa saw a migration of many of the previously-disadvantaged Black majority from rural areas to urban areas in search of employment. This resulted in more than 56% of the population living in urban centres. As a result of the high cost of living in urban centres, people's lifestyles changed drastically and this has led to an increase in the four most notorious chronic diseases, namely, cancer, cardiovascular diseases (CVD), chronic obstructive pulmonary disease and Type 2 diabetes. Furthermore, socio-economic disparities, environmental factors, work stress and low income generation have all contributed to the escalation of non-communicable diseases, including diabetes, among these populations (Ekholuenetale, Wegbom, Edet, Joshua, Barrow & Nzoputam, 2023; WHO, 2019).

Urbanization leads to dense populations in towns and is a major result of westernization; it affects food system sustainability because it limits the size of areas available for meaningful agricultural production. Researchers, such as Ekholuenetale et al. (2023) and Mbogori and Mucherah (2019), note that the westernization of traditional African diets has led to various lifestyle and behavioural changes. This, coupled with reduced levels of physical activity and increased consumption of tobacco and alcohol, has caused changes in dietary patterns, accelerating the spread of chronic diseases in Africa. The above-mentioned researchers indicated that this nutritional transition has led to obesity, which is a major risk factor for Type 2 diabetes in both adults and children. According to Matseke (2023), democratization of South Africa has not only resulted in urbanization but has also seen an increase in migration of health professionals, especially experienced nurses and doctors, from rural to urban areas. This migration of the health workforce has become a critical factor and a burden to the country's health system, weakening access and provision of health services, and hence increasing healthcare inequality between the urban rich and the rural poor (Matseke, 2023; WHO, 2019).

The World Health Organization's report (2020) presenting country and regional data for diabetes, indicates that South Africa has the second largest population of people with diabetes in Africa (12.7% of adults), and the number is expected to increase by more than half by 2030. The report further indicates that in 2016 diabetes and other NCDs contributed to 16% of the total deaths in the country. This is mainly attributed to a lack of awareness of the disease, poor accessibility to proper healthcare and poor adherence to medical prescriptions (WHO, 2020). This is at a time when South Africa is spending massively on healthcare and the issue of diabetes is at the forefront of its political agenda (Huzooree, Khedo, & Joonas, 2019).

Hawthrone and Grzybowksi (2019) affirm that healthcare provision in South Africa has been negatively affected by the high levels of economic inequality. These researchers noted that in 2015 South Africa had a Gini coefficient of 0.63, indicating its economic inequality to be large. The authors add that the Apartheid-era, which lasted for decades, created severe economic and spatial inequalities in South Africa and many communities remain financially excluded even after Apartheid. Meier et al. (2020) and Siegfried, Hopewell, Erasmus-Claassen, and Myers (2022) state that given these challenges, leveraging technological innovations to empower patients to monitor their own health and lifestyles is seen as an appropriate way to narrow the healthcare provision gap. Hence, the use mHealth could be of paramount importance in decreasing health costs while improving people's empowerment. Meier et al. (2020) and the mHealth Strategy report (2019) assert that using mHealth systems for self-monitoring chronic diseases could greatly improve patients' attitudes towards drug adherence, reduce their healthcare costs and improve performance management.

The South African mHealth strategy report (2019) notes that mHealth includes tools that have had a tremendous positive impact on the health of populations around the world, especially in developed countries. The report further indicates that the use of short message systems (SMS) in healthcare has been found to be successful and, therefore, many healthcare organizations endorse this feature. The effective use of mHealth has been found to be of great importance, especially in developing countries that are resource-constrained and have a shortage of healthcare workers (Matseke, 2023; Meier et al. 2020; WHO, 2019). It has been suggested that improvements could easily be supported due to the proliferation of mobile telephones in the developing world, especially in South Africa which has extensive mobile broadband (Asongu & Odhiambo, 2018). This implies that use of mobile devices, such as phones, tablets, computers and tracking devices, could be an ideal way to support and enhance healthcare provision and accessibility in developing countries where mHealth is implemented.

Kruse, Betancourt, Ortiz, Valdes-Luna, Bamrah, and Segovia (2019) declare that developing countries are confronted by several independent barriers that challenge the successful implementation of mHealth. These researchers identify the following common barriers: poor infrastructure, lack of equipment, a population many of whom have a poor social-technological background, language barriers, human resource constraints, time poverty or work conflicts, insufficient budgets, psychosocial issues, lack of standardized policies and strategies, low efficacy and low literacy levels, insufficient training, and threats related to information privacy and confidentiality. Ezezika, Varatharajan, Racine and Ameyaw (2022) confirm that, despite South Africa spending a lot on health care, the challenges of creating and maintaining infrastructure, a lack of equipment, and limited human capacity result in a prevalence of inequality that affects healthcare and the entire health system. Additionally, Blecher and Daven (2020) observed that the South African National Health Insurance (NHI), which is suggested as a way to bring about fundamental transformation in the country's health sector in terms of integration, equity, cost-effectiveness and universality, also faces major hurdles. Impediments include poor implementation due to policy inconsistencies, legislative misalignment, lack of transparency, corruption, and health expenditures beyond those budgeted for. Previously, researchers observed that a lack of standardization and integration has hindered the development of a single framework to be used as a guideline to improve ICT in the South African health sector (Kalema & Kgasi, 2014; Van der Pol et al., 2022).

These problems suggest that innovative solutions are needed to make mHealth a viable alternative to improve healthcare provision in South Africa. Therefore, this study sought to develop a contextual model for a persuasive technological mHealth self-monitoring system for diabetic patients in South African communities. The system developed is intended to empower diabetic patients to monitor their own health and comply with prescribed medication regimes.

1.3 Research Problem

The World Health Organization's report on chronic disease prevalence indicates that these diseases are responsible for the greatest burden of health conditions, leading to disability and death (WHO, 2014, 2019, 2020). The reports further indicate that chronic diseases are no longer restricted to less affluent countries and populations, but also affect higher and middle-class populations. Achoki et al. (2022) asserted that, in addition to identifying risk factors, including prescription of drugs, primary prevention, structural, logistic, human capacity and organisational challenges, there is a need to leverage technology that will monitor patients regarding adherence to the prescribed medication. Numerous researchers (for example, Ezezika et al., 2022; Kruse et al., 2019; Van der Pol et al., 2022) have observed that, despite the many challenges, there have been notable developments in the use of technological innovations and applications, such as mHealth that support healthcare. However, the South African mHealth Strategy report (2019) reveals that most research on health informatics has focused on interventions to provide information to patients, rather than empowering patients to change behaviours leading to adherence to medicine. The lack of empowerment of patients to take care of their lives has highlighted the need for a model that informs a mHealth self-monitoring system (Franklin, Abel, & Shojania, 2020).

Researchers (for example, Gerber, Biggers, Tilton, Smith-Marsh, Lane, Mihailescu, Lee, & Sharp 2023; Istepanian & Al-anzi, 2018; Kwame & Petrucka, 2021) have suggested that the use of mobile technology for patients with chronic diseases, such as diabetes, is necessary to obtain information about their adherence patterns. However, what is available is insufficient, and these patients require constant monitoring to ensure that they adhere to drug regimens. Furthermore, Meier et al. (2020) and Kalema and Mosoma (2019) assert that patients who take medicine routinely require technological support in the form of self-monitoring. Such patients need frequent reminders to take care of themselves, as many could give up knowing that theirs is an incurable disease. The WHO (2020) states that drug inconsistencies have been the leading cause of high mortality rates for people with chronic diseases. Debon, Coleonea, Bellei and De Marchi (2019) report that routine and timely taking of medication suppresses the symptoms and other ailments that could complicate diabetic conditions. These authors stressed that failure to take medication regularly allows additional ailments and symptoms the opportunity to worsen the patient's condition, due to the patient's low levels of immunity. Debon et al. (2019) aver that technological innovations, such as mHealth, should be integrated with persuasive technology strategies that embrace both technology and behavioural change to enhance adherence, and such integration should also take into consideration the cultural context.

Chatterjee (2019) and Aldenaini, Alslaity, Sampalli and Orji (2023) report that the development of a persuasive mHealth system for patients' self-monitoring is still in its infancy and that those systems that are available are useful primarily in the contexts of developed countries. This is because aspects of culture and the social, political, economic and technological background, together with the environmental surroundings of the patients, play an important role in technology use. Huzooree et al. (2019) also found that contextualization of persuasive mHealth self-monitoring models is imperative for positive behavioural change, since cultural groups have varying beliefs, attitudes and norms. These researchers emphasized that persuasive technology could play an important role supporting physical and psychosocial needs and encouraging lifestyle changes and self-management of chronic conditions.

1.4 Goal and Objectives

This study sought to achieve the following goal and objectives:

1.4.1 Goal

The goal of this study was to develop a contextualized model for a persuasive technology mHealth self-monitoring system for diabetic patients in South African communities.

1.4.2 Objectives

To achieve the study's goal, the following objectives were identified:

1. To identify factors that influence the use of mHealth for self-monitoring by diabetes patients in the South African communities
2. To identify technological, psychological, individual, social and external factors that influence diabetic patients' behaviour in interacting with technology
3. To discuss theories and models that could be used when designing persuasive technology mHealth monitoring systems for diabetic patients in South African communities
4. To use the Design Science methodological approach to develop an artifact for a persuasive mHealth self-monitoring system for diabetic patients in South Africa communities

1. 5 Research Questions

1.5.1 Primary research questions

The primary research question was:

How can a contextualized model be developed for a persuasive technology mHealth self-monitoring system for diabetic patients in South African communities?

1.5.2 Secondary research questions

This study sought to answer the following secondary questions:

1. What factors influence the use of mHealth for self-monitoring by diabetes patients in the South African communities?
2. What technological, psychological, individual, social and external factors influence diabetic patients' behaviours with regard to interaction with technology?
3. What theories and models should be used in the design of persuasive technology mHealth monitoring systems for diabetic patients?
4. How can a Design Science methodological approach be used to develop an artifact for a persuasive mHealth self-monitoring system for diabetic patients in South Africa communities?

1.6 Overview of the Methodological Approach

This section provides an overview of the methodology used by this study to facilitate the collection and analysis of data. The detailed research design and methodology are presented in Chapter 4 of this thesis.

This study allowed the triangulation of methods by using positivism and Design Science Research (DSR). A sequential strategy was adopted together with the quantitative approach to develop a model that informed the architectural design that in turn formed the basis for the experimental design of the artifact. Healthcare self-management research requires the study of complex, multilevel processes and systems that may require the use of either or both a quantitative or a qualitative approach and experimental methods (Dobson, Whittaker, Murphy, Khanolkar, Miller, Naylor & Maddison, 2017; Larbi, Bradway, Randine, Antypas, Gabarron, & Årsand, 2019). Methods are chosen based on the nature of the research objectives or questions. In the case of this study, quantitative methods were used to determine causality, generalizability, and the magnitude of effects of the factors influencing the use of mHealth for self-monitoring. On the other hand, a Design Science approach was used to jointly address the technological aspects and behavioural aspects to form a single integrated architecture that was intended to trigger an occurrence of one or more phenomena. The use of triangulation of methods in this study is innovative, addressing contemporary healthcare issues by combining the qualitative and Design Science approaches.

1.6.1 Data collection

Due to ethical restrictions, quantitative data were collected using close-ended questionnaires from healthcare and associated service providers and included social workers and medical professionals. After identifying healthcare facilities from which data could be collected, simple random sampling was used to select respondents to whom the questionnaire could be distributed. The completed questionnaires were screened for completeness and entered into the Statistical Package for the Social Sciences (SPSS v 27) and later exported to Smart Partial Least Squares (SmartPLS) for analysis.

1.6.2 Reliability and validity

The internal consistency reliability was measured using Cronbach's Alpha (α) to determine the extent to which the questionnaire items measured the intended constructs of using mHealth for self-monitoring of diabetic patients. As indicated by Tamilmani, Rana and Dwivedi (2021), constructs whose reliabilities were above the recommended threshold of 0.7 were qualified for further analysis. Furthermore, constructs whose reliabilities were below 0.5 were used after modification of their interrelatedness and homogeneity (Ringle, Wende & Becker, 2022). Additionally, since this study employed variance-based Structural Equation Modelling (SEM), composite reliability, average variance extracted and discriminant validity using the heterotrait-monotrait ratio (HTMT) were measured when fitting the measurement model based on the Fornell and Larcker (1981) criteria.

1.6.3 Data analysis

After testing for reliability and ensuring validity, the data was analysed using SmartPLS for variance-based SEM. This study opted to use variance-based SEM for various reasons, which included its ability to directly determine the interacting effects of moderating factors, its flexibility to perform SEM with data sets less than 200 as opposed to traditional covariance-based SEM, as well as its potential to compute discriminant validity using the HTMT function that does not exist in covariance-based SEM, which requires hard mathematical computations.

1.6.4 Ethical consideration

This study followed the UNISA ethical guidelines and hence the proposal and measuring instruments for data collection and the informed consent documents were reviewed and approved by the ethics committee. In addition, ethical clearance was obtained from each province where the data was collected. These ethical considerations guided the data collection, analysis and dissemination of the findings.

1.7 Justification of the Study

The new paradigm of diabetes management emphasizes cardiorenal risk reduction and weight management in addition to focusing on glucose control and the prevention and management of microvascular and macrovascular complications with non-glucose lowering agents (Grundlingh, Zewotir, Roberts, & Mand, 2022). The prescription of diabetes medication for a patient's glycemic control requires significant cognitive reframing to enable patients make informed decisions about their health. Recent developments indicate that the management of diabetes has been revolutionized by technological interventions in both treatment and adherence as well as for continuous glucose monitoring, insulin pump therapy and telehealth (WHO, 2019). Although there have been major advances in the development of mHealth technologies for diabetes care in the last decade, there are still major challenges in both the technical and clinical areas (Amalindah, Winarto & Rahmi, 2020). These require that further research and work be carried out for the development of mHealth systems intended to assist diabetic patients to manage their lives as well as to adhere to medical prescriptions.

The burgeoning development of ubiquitous and pervasive technology has been extensively built upon to facilitate healthcare provision and monitoring. Technological applications such as mHealth have come under the spotlight as an effective tool for healthcare monitoring of both patients and medical personnel (Islam, Lambert, Islam et al., 2021). For example, MHealth has been used as a communication tool to disseminate information in the form of simple messages and alerts or reminders to assist patients in adhering to treatment. However, as also noted by researchers (such as, Aldenaini et al., 2023; Chatterjee, 2019; Huzooree et al., 2019), the major impediment to successful mHealth usage is contextualization that embraces aspects of language and culture. Because adherence to a medication regimen involves a change in lifestyle or behaviour adjustment, patients need effective motivation in order for the technology triggers to change their behaviour (Fogg, 2009). This explains the need to moderate behavioural intention by introducing mediating and motivating factors when developing a model for an mHealth self-monitoring system.

Researchers, such as Islam et al. (2021), have observed that mHealth technologies have been largely leveraged to manage disease outcomes, including chronic diseases (for example, diabetes, hypertension, and other CVDs, maternal health, and psychological disorders). These researchers confirm that mHealth has the potential to empower patients, health workers and health system managers to manage healthcare efficiently and effectively by providing guidelines, procedures and, to an extent, referral services in real-time. The researchers mentioned above claimed that, when mHealth is used effectively, it will also serve as a reminder to patients of the need for self-management and self-administration of medical prescriptions, thereby improving medication adherence. However, self-management and administration of medical prescriptions both involve behavioural change, hence the mHealth system that is intended to work as a reminder should include one or more components that consider human behaviour (Debon et al., 2019; Arsenijevic, Tummers & Bosma, 2020). These authors proposed a model that integrates the use of technological applications, such as mHealth, and factors addressing human behaviour in the form of a persuasive system.

The use of digital interventions for chronic disease management is increasing dramatically and has led many companies to manufacture wearable devices and mobile applications that can be used in healthcare to collect health data (Kwame & Petrucka, 2021). It is from this perspective that the concept of self-monitoring is viewed when mHealth devices and applications are used as reminder systems. Quantified self-help devices help individuals to track physiological, behavioural and biological events as well as recording exactly when they responded to technological applications. Fogg (2020) notes that the adoption and use of wearable devices and mHealth applications by individuals can only be effective if such devices produce a new stimulus or signal that in turn causes the individual to respond to the technology as if it were another human being. Studies of using persuasive technology in healthcare interventions have been based on earlier research by Nass, Fogg, and Moon (1996) and Fogg (2002). These papers revealed that there is a need for the integration of technology with behaviour determinants to produce effective use of technology for health self-monitoring.

Unlike in the case of other diseases, patients with chronic diseases such as diabetes require regular disease management appointments and attentive follow-up to reduce the risk of adverse health outcomes. This implies that there is an urgent need for technological innovations facilitating healthcare monitoring of chronically ill patients. These patients rely on lifelong healthcare systems, which include various stakeholders (such as healthcare professionals, social workers, primary care providers, specialised care centres, and community-based helpers) (Gqalenil & Mkhize, 2023; Moses et al., 2021). The recent COVID-19 pandemic constrained hospital healthcare systems due to the travel restrictions, social distancing and lockdowns in effect. Hence, the pandemic reduced patients' access to hospitals, and in many cases worsened their medical conditions - many people lost their lives, especially those in low-resource settings (Fekadu, Bekele, & Tolossa et al., 2021). The restrictions on movement during the pandemic also made follow-up on patients with chronic diseases even when medical services had been declared to be essential. Hence, COVID-19 and its subsequent fallout provide strong supporting evidence for the use of mHealth for self-monitoring of chronically ill patients.

1.8 Contributions of the Study

The contribution this study makes is threefold; theoretical, practical and methodological.

1.8.1 Theoretical contribution

Currently, all countries, developed or developing, have been faced with the worldwide COVID-19 pandemic that claimed many lives and strained numerous healthcare systems. Available literature reports that before the advent of COVID-19 developing countries, including South Africa, were facing a double burden of infectious and chronic diseases (Achoki et al., 2022; Akindele & Useh, 2021). Many of these countries, for instance those in equatorial regions, also faced traditional health hazards, such as malaria and measles, which have high mortality rates for both adults and children under the age of ten (Bradshaw et al., 2019). Worldwide, there is an increasing prevalence of lifestyle-related chronic diseases such as diabetes (Ekholuenetale et al., 2023). Because these diseases require regular medication, patients need frequent automatic reminders to take their medicine to suppress the main disease and related ailments. This study sought to develop a contextualized mHealth self-monitoring model that leverages persuasive technology, where a device is used as part of the implementation of a reminder system for patients with diabetes. The development of this contextualized mHealth self-monitoring model is a significant theoretical contribution. Various studies have called for such a model, and future researchers may use the model in extended research into mHealth self-monitoring systems.

1.8.2 Practical contribution

The WHO (2020) confirms that the high mortality rates due to chronic lifestyle diseases are because of lack of awareness and poor adherence to medical prescriptions. The report further says that there is a worldwide effort to fight diabetes although the disease is still claiming many lives. The developed model is expected to be used as a cornerstone for management and research in the ongoing debate regarding ways to fight diabetes. The model will support the implementation of a mHealth self-monitoring system so that patients are empowered to actively join the fight against this killer disease. Therefore, this study makes a significant practical contribution to healthcare care management not only in South Africa but also in other developing countries.

It is worth noting that diabetes is a difficult disease to manage since it requires daily, if not more frequent, monitoring along with behavioural change (Shaw, Yang, Barnes, Hatch, Crowley, Vorderstrasse, Vaughn, … Steinberg, 2020). In order to control diabetes risk factors, patients must adapt their diet, physical activity and medication dosage based on blood glucose values and as prescribed by the healthcare personnel. The mHealth self-monitoring system developed in this study is intended to facilitate self-management among diabetic patients by reminding them to adhere to the medicine schedule, reporting the patients' trends in taking medicine to healthcare providers, and by providing health-related information and direct feedback to patients. Monitoring patients behaviour in near real-time and transmitting reports to healthcare providers, can foster collaborative work and modify care delivery. By so doing this study will be making a significant practical contribution to diabetes healthcare delivery and patients self-management.

1.8.3 Methodological contribution

The philosophical perspective of this study was based on the challenge of developing a contextualized mHealth self-monitoring model to empower diabetic patients to take control of their own lives. This problem could be addressed by investigating both theory and experimental experiences. Therefore, this study used a Design Science approach which involved developing an artifact that can be integrated into a fully-fledged self-monitoring system. The development of an artifact is a significant methodological contribution to the body of knowledge of Information Systems, in which experimental and theoretical approaches were combined to solve a research problem. This study developed a model that was quantitatively validated using Smart-PLS Structural Equation Modelling. The model was integrated into an artifact using the Design Science methods. The artifact was quantitatively evaluated using expert reviews. This triangulation of scientific methods can be used by future researchers to extend research into artifact development and modelling in Information Systems. In so doing this study will be making a significant methodological contribution.

1.9 Outline of the Study

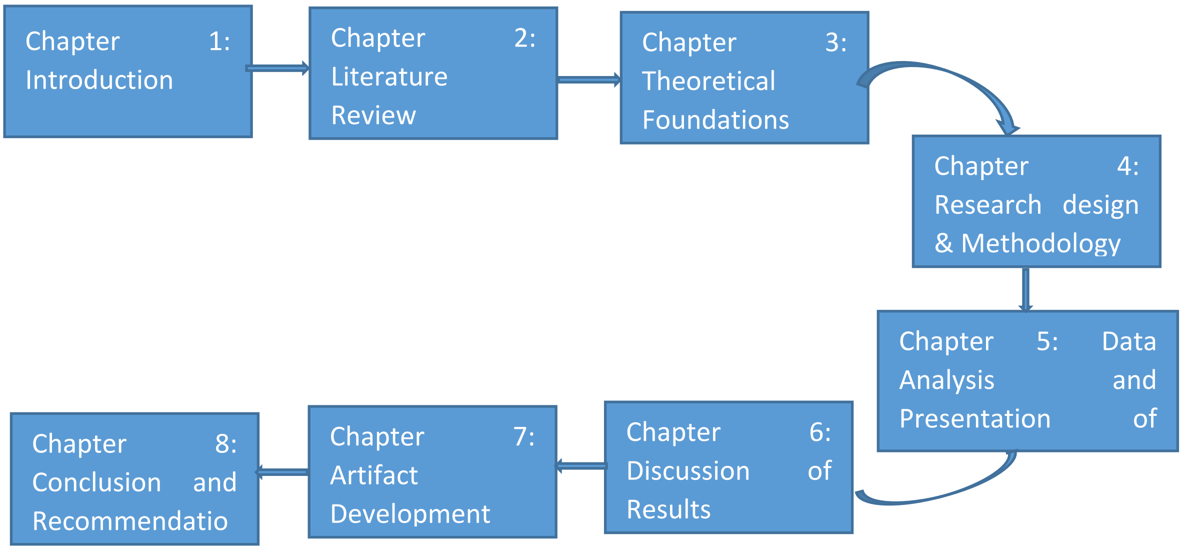


Figure 1.1: Thesis Outline

This section gives a brief explanation of what is presented in each chapter of this thesis by giving a summary of each chapter. The graphical representation of the activities in each chapter is illustrated Figure 1.1.

Chapter 1: Introduction This chapter introduced the concept of mHealth usage for health monitoring. The chapter also presented the background to the study. The motivation that led to this study was highlighted, leading to addressing the study problem presented. The objectives and research questions follow the problem statement and will be answered in this study. The chapter gives a justification for the proliferation of studies of self-monitoring of mHealth, especially after the advent of COVID-19. The justification for the study is followed by the presentation of the contribution that this study makes, and finally a research outline is presented.

Chapter 2: Literature Review The second chapter presents the literature referred to by the study researchers. The chapter presents the concept of mHealth, its benefits, and challenges in its implementation. Next the chapter presents a discussion of the burden of chronic diseases from three different perspectives, namely, worldwide, in sub-Saharan Africa, and in South Africa in particular. This is followed by a discussion of factors that influence the implementation of mHealth. The chapter also presents related work, in which mHealth self-monitoring and persuasive technology are elaborated.

Chapter 3: Theoretical Foundations This chapter of discusses the theoretical perspectives that relate to this study. First, the chapter discusses theories and models relating to technology acceptance, adoption and use. Secondly, the chapter discusses various behavioural change theories. Lastly, the chapter sheds light on the theory underpinning this study. Based on the underpinning theory, a conceptual model is drawn and hypotheses requiring testing are highlighted.

Chapter 4: Research Design and Methodology This chapter first discusses the philosophical understanding of the research. That leads to a discussion of the ontology, epistemology and the methodology followed by the study. The chapter describes the two phases during which the study was conducted, namely, Phase 1 that dealt with the quantitative approach that sparked the artifact design, and Phase 2 which was the designing of the artifact. The two phases are presented step by step in this chapter.

Chapter 5: Data Analysis and Presentation of Results This chapter presents the results obtained from the quantitative phase (Phase 1). First the frequencies of the demographic and situation variables are provided. This is followed by the correlation and regression analysis and by an analysis of the interacting effects of the moderating factors.

Chapter 6: Discussion of Results This chapter presents the results that were obtained from data collected and analysed using the quantitative method in Phase 2, before discussing the implications of the findings. The chapter discusses the findings in relation to the research objectives and goal and then in relation to the tested hypotheses of the study.

Chapter 7: Artifact Development This chapter describes the step-by-step design and development of the artifact. The chapter discusses the link between the model developed and the artifact and how one feeds into the other. It focusses on the mHealth model developed for self-monitoring, and how this evolved into an abstract architectural design of the artifact on which the mHealth was based. Lastly, the chapter outlines how the artifact was evaluated.

Chapter 8: Conclusion and Recommendations This final chapter gives a general overview of the study, indicating lessons learnt and describing in a general form the contributions that the study makes. The chapter then presents the limitations of the study based on which the direction for future research is given. Lastly, the chapter highlights the recommendations that the study makes to researchers and policymakers.

1.10 Summary

Diabetes is one of the world's most fast-growing epidemics and is a leading cause of death around the world. Its prevalence has been furthered by increasing globalization and urbanization that has seen many people migrating to urban areas and the associated more sedentary lifestyle, higher consumption of unhealthy food as well as physical inactivity. Additionally, the effect of socioeconomic status in many developing countries on the prevalence of diabetes is very evident and arises from health inequalities, poverty and lack of employment.

This chapter discussed the effects of chronic disease, in particular diabetes, and its burden on the health systems of developing countries. It emphasized the challenges faced by the South African healthcare system. Additionally, the chapter highlighted the research problem the study sought to address, the set objectives as well as justification of the study. Furthermore, the contributions the study makes were discussed and lastly the chapter gave the outline of the entire thesis.

CHAPTER 2: LITERATURE REVIEW

This chapter discusses published literature related to the topic of this study; it includes a detailed discussion of the concept of mHealth, its benefits, and factors influencing its implementation. The chapter also considers existing reports and publications related to mHealth self-monitoring. It highlights gaps that exist and calls for more research. Based on the related work, the chapter elaborates the theoretical foundations from which a conceptual model was developed. Finally, the chapter highlights the hypotheses that were drawn from the operationalization of the constructs.

2.1 Health Systems

A health system, also known as a healthcare system, includes the people, institutions and resources that deliver healthcare services and the products required to meet the health needs of a given population (Bacelar-Silva, Cox III & Rodrigues, 2022). Worldwide, health systems vary according to national structures and settings. This implies that countries design their healthcare systems depending on their specific needs and available resources. However, there are common elements in all health systems, and these include primary healthcare and public health measures (Rensburg, 2021). To ensure diversity and equality in the provision of healthcare, nations must ensure that four basic functions are carried out. These are financing, provision, stewardship and resource development (such as the development of human resources and physical infrastructure, and knowledge dissemination) (Bacelar-Silva et al., 2022). The effective performance of these functions is essential to enable the healthcare system to be sufficiently responsive and to improve its accessibility (Kendzerska, Zhu, Gershon et al., 2021).

A high degree of responsiveness by healthcare is imperative regardless of the economic position of the country. Rensburg (2021) proposes that a country must find an effective way to promote equal availability and access to the healthcare system by all citizens regardless of their geographical location. This requires bringing services reasonably close to communities, especially to those that are not easily accessible by health workers. Achoki et al. (2022) contend that increasing the accessibility of healthcare is key to solving healthcare inequality and reduces the gap between the urban rich and the rural poor. The use of ICT and its application, such as for electronic health (e-health) and mHealth, in the delivery of healthcare has been motivated by efforts to improve accessibility and availability of healthcare systems (Arsenijevic et al., 2020; Ezezika et al., 2022; Shaw et al., 2020).

2.1.1 The South African health system

In 2019 South Africa's population was estimated to be more than 58.5 million, the majority of whom access health services through government-run public clinics and hospitals (Massyn, Barron, Day, Ndlovu & Padarath, 2020). The South African healthcare system encompasses the public sector which is run by the government, and the private sector which is controlled by individuals and independent organizations. The provision of government healthcare services in South Africa is divided into three categories, primary, secondary and tertiary healthcare, all of which are controlled at the provincial level. However, while South Africa allocates a large proportion of the national budget to healthcare, unfortunately the healthcare system is widely considered poor and unequally distributed (Blecher & Daven, 2020). The country also lacks a systematic means of monitoring the emigration of its healthcare professionals to other countries, even though its relatively good economy in turn attracts healthcare professionals from other countries (Moses et al., 2021).

The capabilities of healthcare systems are widely determined by how able they are to mitigate health challenges and the turnaround time for challenges to be addressed (Hawthrone & Grzybowksi, 2019). Hence, the provision of services depends to a great extent on the sufficiency of the workforce in terms of numbers and quality of skills and expertise, as well as their availability, and how and where they are deployed (Rensburg, 2021). In South Africa, for example, the post-Apartheid era (since 1994) has seen increased urbanization due to the movement of people to urban areas. This changed spatial settings and constrained the urban healthcare systems. However, at the same time the provision of resources to rural settings was reduced to accommodate the influx to urban settings (Bradshaw et al., 2019; Kalema & Mosoma, 2019). The effect of increased urbanization became even more evident with the advent of COVID-19 as it increased the risks of patients with chronic complications due to poor monitoring and lack of access to medical facilities. Many people with chronic diseases and associated complications were unable to access their healthcare facilities and medication due to lockdown and social distancing. This poor accessibility worsened the situation of individuals with severe and chronic illnesses and hence the health of these victims deteriorated and in the worst case, some patients died (Arsenijevic et al., 2020; Rensburg, 2021).

2.1.2 Challenges of the South African health system

The South African government has endeavoured to allocate a reasonable budget and a good percentage of its gross domestic product (GDP) to health with quality healthcare being a constitutional obligation in the country (Blecher & Daven, 2020). To increase the effectiveness and efficiency of healthcare delivery, as well as to ensure compliance with quality standards, the government introduced a variety of developmental programmes, health policies and legislation. However, these efforts have been met with impediments that have led to the national healthcare system being labelled the most inefficient in the Southern African Development Community (SADC) region and there have been loud calls for its overhaul (Maphumulo & Bhengu, 2019). Previous researchers attributed South African healthcare challenges to the Apartheid period (1948-1993), during which time healthcare provision and health facility allocations were based on discriminatory spatial distribution and race (Akindele & Useh, 2021; Ekholuenetale et al., 2023). However, later studies have attributed these challenges at least in part to a lack of integration of ICT into the health system, poor monitoring of both healthcare workers and patients, as well as lack of contextualization of electronic health system frameworks (Blecher & Daven, 2020; Debon et al., 2019; Kalema & Mosoma, 2019; Siegfried et al., 2022).

Although the South African government has greatly improved its healthcare system and much has been achieved post-Apartheid, millions of South Africans still suffer from preventable harm, including communicable chronic diseases, accidents and infectious diseases that have kept the mortality rate high (Kalema & Mosoma, 2019; Massyn et al., 2020; Narsai et al., 2022). These challenges were worsened by the COVID-19 pandemic that weakened the country's primary healthcare network, which already had limitations due to a lack of human and other resources (Blecher & Daven, 2020). The World Health Organization has indicated that, much as the constitutions of many developing countries state that every citizen has the right to healthcare, there is limited enjoyment of this right by all citizens (WHO, 2019). For example, South Africa's response to the COVID-19 pandemic in terms of access to treatment, testing and vaccination was first provided to the urban rich and those who could pay or had good medical insurance (Fekadu et al., 2021).

In response to the health challenges, the South African healthcare system needs to be supported by technological innovations, such as mHealth, that can be leveraged to reach the people living in rural disadvantaged communities (Istepanian & Al-anzi, 2018; Maphumulo & Bhengu, 2019). Therefore, governments, policymakers and healthcare institutions should support innovative electronic healthcare systems including mobile self-monitoring systems to reach patients who need constant care.

2.2 The Burden of Chronic Diseases

Worldwide, chronic diseases such as diabetes, heart disease, stroke and cancer are major causes of morbidity and mortality (Narsai et al., 2021). Chronic diseases are major causes of illness, disability and death worldwide and have led to a serious health and economic burden, especially in low- and middle-income countries (Akindele & Useh, 2021). Chronic diseases are becoming both more prevalent and more expensive to treat as people live longer; globally, they are predicted to cost $47 trillion by 2030 (Mahumud, Gow, Mosharaf, Kundu, Rahman, Dukhi, Shahajalal, Mistry, Alam, 2023). The management of chronic diseases is highly influenced by individual lifestyle, behaviour and environmental factors in a community. Factors like physical inactivity, poor nutrition, tobacco use and excessive alcohol consumption have been highlighted as major risk factors for these conditions (Achoki et al., 2022; Hacker, 2024; WHO, 2019, 2020). Investment in prevention in terms of influencing both the lifestyle and social determinants remains small compared to treatment. Therefore, technology and pharmaceutical innovation, together with a concomitant investment in prevention and monitoring of chronic disease patients are crucial.

Developing countries, especially those in Africa, are undergoing both epidemiologic and demographic transitions that have increased the burdens related to infectious and chronic diseases coupled with other socioeconomic inequalities occurring in predominantly rural populations (Achoki et al., 2022; Akindele & Useh, 2021). In South Africa for example, chronic diseases account for approximately 61% of the total burden of disease and 54% of annual mortality, with diabetes, cardiovascular disease, chronic respiratory disease, cancer and stroke being the most common (Bradshaw et al., 2019; Massyn et al., 2020). Even though South Africa spends a lot on healthcare, many serious challenges exist that hinder effective management of the situation. Among them are the unregulated private health sector and a constrained public health system (Kalema & Musoma, 2019; Massyn et al., 2020). Also, the majority of the South African population (over 70%) still reside in rural areas and have minimal access to formal healthcare services due to an urban treatment funding bias and the need for out-of-pocket expenditure and little or no health insurance coverage amongst this group of people (Akindele & Useh, 2021; Ekholuenetale et al., 2023; Maphumulo & Bhengu, 2019).

2.2.1 Diabetes and it prevalence in South Africa

Diabetes mellitus (diabetes) is a metabolic disorder that either makes a body resistant to the effects of insulin or the body fails to produce enough insulin to process glucose (Grundlingh et al., 2022). Consequently, this leads to an accumulation of sugars, and this causes serious health complications (Shaw et al., 2020). Diabetes was the second leading underlying cause of death in South Africa in 2016 and 2017 and this situation has become even more serious as the rate almost tripled from 4.5% in 2010 to 12.7% in 2019 (Grundlingh et al., 2022; Mahumud et al., 2023). The increasing incidence of diabetes and obesity saw South Africa being ranked as the unhealthiest country on earth by the Indigo Wellness Index in 2019 and this forced the South African government to impose a sugar tax in 2018 (Grundlingh et al., 2022).

According to Gerber et al. (2023), patients suffering from diabetic complications often become reluctant to take their medicine. However, the reasons for nonadherence are multifactorial and sometimes difficult to identify. Researchers (such as, Alfaleh, Alkattan, Alzaher, Alhabib, Alshatri, Alnamshan, Almalki …………… Ibrahim, 2023; Chang, Tu, Chiou, Lai, & Yu, 2022) have noted that nonadherence by diabetic patients may be attributed to numerous factors (age, perception and duration of disease, information, psychological factors, complexity of dosing regimen, polytherapy, safety, tolerability and cost). Hence, for better management of the disease, various measures need to be put in place to increase patient satisfaction and increase adherence (Abbasinia et al., 2020; GqaleniI & Mkhize, 2023). Such measures may include, but are not limited to diabetes self-management education, information sharing, psychosocial and goal-based behavioural support, and coordination of care. Adherence for diabetes patients is essential as it reduces the cost of managing complications by lowering blood glucose levels in addition to correcting hypertension and dyslipidaemia (Grundlingh et al., 2022).

Diabetic complications not only affect the health of the patients suffering from them, but also have a serious financial implication for their family due to the regular need to buy medicine as well as keeping the patient and other family members from work with a resultant loss of earnings (Joensen, Fisher, Skinner, Doherty, & Willaing, 2019). Diabetes also negatively impacts the country's economic growth as its strains the healthcare budget, and hospitals need to be equipped with sufficient suitable resources including for monitoring the patients. Additional monitoring of patients suffering from complications is extremely important, as a lack of vigilance may worsen their conditions leading to further complications and death (WHO, 2019; Lin et al., 2022). Hence, timely social interventions are essential, including regular awareness campaigns, controlling and monitoring diabetes patients, and leveraging technological innovations like mobile health for self-monitoring.

2.3 Mobile Health

The South African mHealth strategy (2019) describes mHealth as a form of mobile computing used to deliver health-related services, and to support medical personnel when interacting with patients. The proliferation of ICT, and the increasing use of mobile telephony, continues to provide an accessible medium of communication for healthcare providers and patients. This has led to the advent of patient monitoring by means of cell phones, portable digital assistants (PDAs) and other wireless devices. Kumar et al. (2023) say that mHealth is the fastest-growing subset of eHealth due to the continuous evolution of mobile technology platforms. mHealth has been key in empowering patients with information, improving the accessibility of health services and improving real-time data management.

2.3.1 mHealth monitoring of patients

The WHO (2020) report covering country and regional diabetes data indicates that diabetic patients need exceptional care despite numerous challenges, such as inaccessible specialists and educators to provide behaviour counselling, high patient volumes, poor adherence to medications, and inadequate motivational support for proper disease management. Little or no follow-up of diabetic patients results in high rates of diabetes-related complications, increased healthcare costs, and a decline in the quality of patient lives (Ashrafzadeh & Hamdy, 2018). Such care includes reminding patients of their routine medication schedule and the 'dos and don'ts' for a diabetic patient, and encouraging patients to perform physical activities. As Arshed et al. (2023) noted, the high mortality rate of chronic lifestyle diseases is mainly due to patients' carelessness, incorrect treatment, and problems associated with medicine usage. Gerber et al. (2023) state that, because diabetes specialists are few and those available are overwhelmed with work, remote health monitoring has emerged as a feasible alternative way to prevent diabetic complications.

Huzooree et al. (2019) conducted a systematic review of the literature on mobile healthcare monitoring systems by reviewing articles from 2011 to 2016. These researchers revealed that there are significant influencing factors that must be contextualized for effective mHealth monitoring to occur. Kumar et al. (2023) say that mHealth monitoring would be more successful if factors such as organizational culture, top management support, technology-related issues (such as mobile infrastructure) and individual factors (including education and skills, attitudes, beliefs and norms) are addressed. These authors also note that additional factors, such as technology acceptance and patient characteristics (such as age, socioeconomic and educational status), also demand attention. Researchers (for example, Kalema and Mosoma (2019), Meier et al. (2020), Siegfried et al. (2022)) support a view that the use of mHealth for patient monitoring is similar to the use of any other technology. Hence factors such as culture, government support, availability of finances and technologies, compatibility, scalability, as well as interoperability between health systems, are relevant. However, Chatterjee (2019) and Aldenaini et al. (2023) emphasize that, for the effective empowerment of patients in the medical process, there is a specific need to leverage persuasive technology that combines the use of technology with the patient's behaviour in responding to drug adherence.

2.3.2 Persuasive technology mHealth monitoring

According to Fogg (2002), people may at times respond to computers as though they are living beings, mainly because social responses to certain types of computing systems are automatic and natural. He notes that individuals are hardwired to respond to signals in the environment that seem alive in some way and such responses are instinctive rather than rational. This implies that computers can play a beneficial role as persuasive social actors capable of rewarding individuals with positive feedback, modelling a desired behaviour or attitude, and providing social support (Nass et al., 1996; Xu & Lombard, 2017). Fogg (2020) also noted that, when human beings perceive social presence, they naturally respond in social ways that may include feeling empathy, being angry or performing a social task. This same author adds that providing social cues via computing products is possible and they trigger automatic responses in individuals. Hence, a given behaviour will occur when a motivation, an ability, and a prompt come together simultaneously.

Chatterjee (2019) posits that the fact that humans respond socially to computer products has significant implications for persuasion and is of paramount importance for mHealth self-monitoring of patients with chronic diseases. Aldenaini et al. (2023) add that in mHealth self-monitoring of patients, the mobile device plays a role (persuasion dynamics) similar to social influence arising from social situations. Earlier researchers (for example, Nass et al. (1996), Fogg (2002), Xu and Lombard (2017)), found that affiliation and social identity effects evident in human-computer interactions make human beings on teams with computers behave similarly to the way they would on teams with other humans in terms of the physical and psychological responses, social dynamics, social roles and language. This implies that lifestyle changes encouraged by the use of computer-based applications, such as mHealth, are noteworthy; technology can be used to send simple messages and alerts that aid patients in adherence to treatment (Debon et al., 2019). In addition, providing direct communication through a multimodal content mHealth tool is of significant value for higher adherence to the routine use of the medicine by patients (Arsenijevic et al., 2020).

Fogg (2020) explains that persuasive technology incorporates psychological insights into the design of products, such as mobile apps and wearables, in order to modify people's habits and beliefs. Therefore, according to Fogg's theory the design process should take into consideration factors such as ability and motivation, where motivation arises from one's yearning for social connection. This implies such individuals must have the ability to easily do what the app wants them to do; this is termed self-efficacy and ease-of-use in many technology acceptance and use models. This insight has been a foundation for the development of mobile self-monitoring systems (Aldenaini et al., 2023; Chatterjee, 2019). The persuasive technology approach has been widely used in design and is evident as prompting features, for example, the notifications of reminder systems (Huzooree et al., 2019; Arsenijevic et al., 2020).

2.4 Limitations of Existing Mhealth Self-Monitoring Systems

There are several potential advantages to using mHealth tools because they can facilitate better patient-healthcare provider interactions. However, researchers have indicated that, although the advantages of using these tools in healthcare are well documented, there are still problems related to their successful implementation for self-monitoring (Arsenijevic et al., 2020; Debon et al., 2019; Kruse et al., 2019; Mahmood et al., 2020; Siegfried et al., 2022). Literature indicates that these issues range from insufficient contextualisation, not considering the cultural perspectives and environment of patients enough, to finding effective way of empowering of patients to take care of their own lives (Gerber et al., 2023; Kwame & Petrucka, 2021; Meier et al., 2020).

Another challenge is the lack of an integrative approach for assessing the impact of mHealth applications on the self-management practices among chronic disease patients (Mano, 2018; Chang et al., 2022). Research on interacting factors and situational variables reveals that the form and extent of use of technology can vary, depending on the socioeconomic characteristics of individuals, personal health conditions, demographic variables such as gender and age, level of education, and motivation (Venkatesh et al., 2012; Sheng & Simpson, 2013; Jayeola, Sidek, Abdul-Samad, Hasbullah, Anwar, An, …………. Ray, 2022). These factors not only shape the likelihood of using mHealth but also the actual need for increased self-monitoring. However, many studies on self-monitoring for mHealth have paid little or no attention to examining these interacting effects. Self-monitoring is a continuous process that can broaden or fade with time.

Chronic diseases, such as diabetes, are often linked to a pronounced need to perform certain daily routines, for instance, taking medicine. Carrying out this routine helps to lower sources of dysfunction or feelings of disease. Istepanian and Al-anzi (2018) and Gerber et al. (2023) state that, in addition to the political and clinical challenges that lead some medical personnel to resist technology, other issues require further research. These researchers identify these as limited research on the influence of patient culture and technology efficacy, long-term patient compliance and continued use, and the inclusion of persuasive technologies to achieve desirable changes in behaviour. Shaw et al. (2020) observe that taking care of security and privacy issues is another important aspect of the development of mHealth self-monitoring models and systems. The purpose of this study was to integrate these core aspects to enhance a greater usage of mHealth self-monitoring systems for future digital diabetes care and management.

2.5 Related Work

Several studies have been conducted on mHealth self-monitoring. However, to ensure the novelty and relevance of the literature to this study, an artificially intelligent tool, “Litmaps”, was used to generate a set of recommended articles and also to show how they link with each other. The tool was set up to search for a combination of key words 'mHealth', 'mHealth self-monitoring systems', 'mHealth self-monitoring systems for diabetic patients', and 'mHealth self-management of chronic diseases'. These words and phrases were selected from electronic databases of published articles and conference proceedings, online databases for theses, as well as reference lists of relevant reports and reviews for eight years ranging from 2016 to 2023.

The search revealed that the Dobson et al. (2017) study on mHealth for self-management support was a key paper and had had a wide impact on self-management research on mHealth. In addition, the Dobson et al. study has been cited by many other researchers conducting studies on self-management or monitoring of mHealth. Therefore, that study was used as 'the seed' article. In addition, the search found 20 top-rated articles based on the impact they have had on the domain of mHealth research -

this was based on the number of citations they had, their relevance and novelty. However, among these identified articles, there were eight older articles considered to be outside the specified range. The tool identified them according to their relevance and the number of times they had been cited by other researchers on self-monitoring of mHealth. These old articles were published between 2006 and 2012 and were removed from the related work discussed in this thesis. They were replaced with newer papers even though they had fewer citations. Figure 2.1 shows the seed map for these most prominent articles, with recent articles shown to the right. This section discusses each of these studies chronologically, giving identified limitations and recommendations.

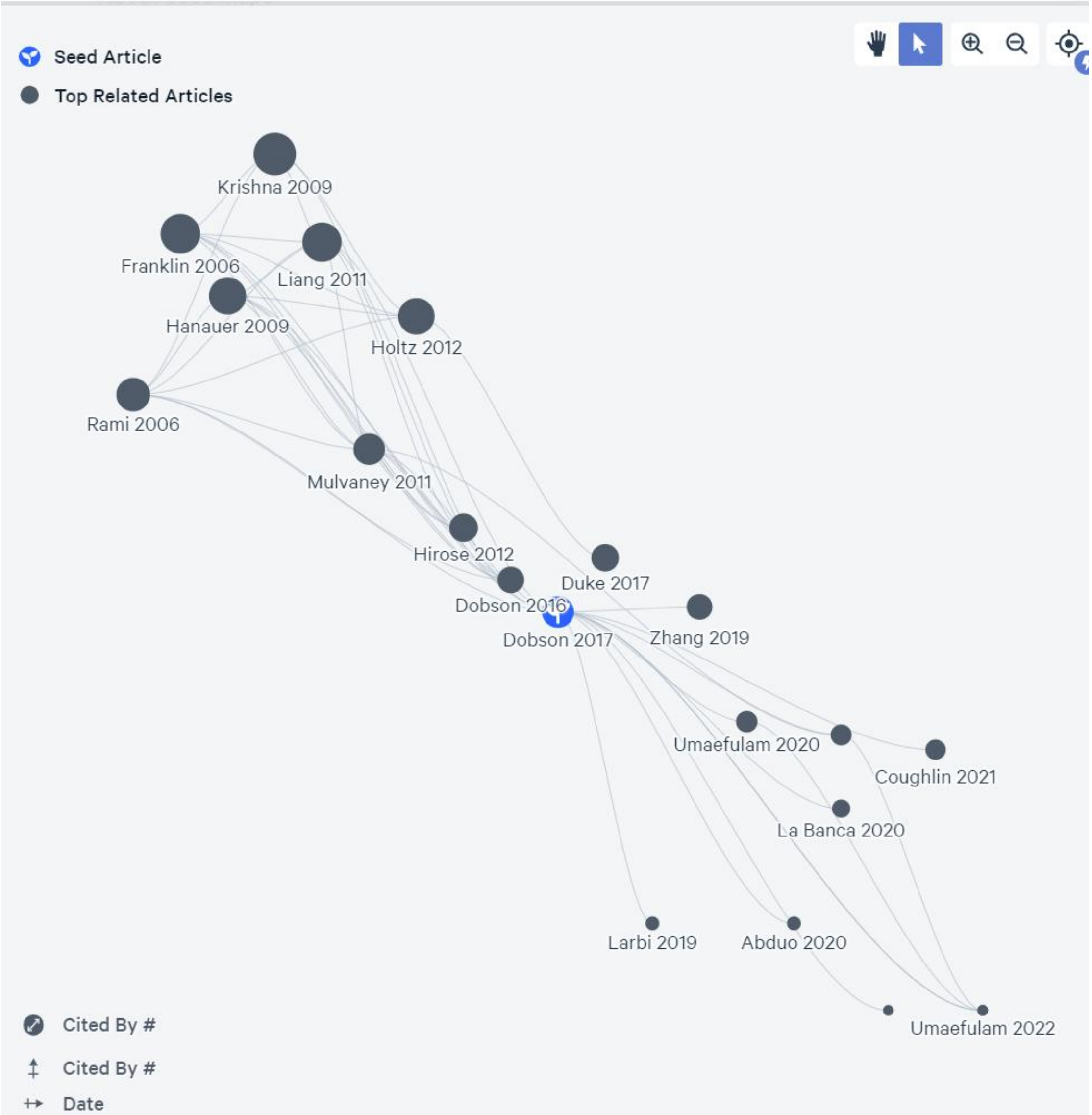


Figure 2.1: Seed Map of Top 20 Related Articles

It is worth noting that, even though the use of Litmaps as a tool for literature search has benefits for a systematic literature review, it is not free from limitations. Firstly, the trial version limits the search to 20 articles whereas the paid up version has unlimited number of outputs. Hence, researchers using the trial version should support the search with a manual search from databases and search engines. Secondly, the permutation of the phrases for the search might also present a challenge as a good permutation will yield better results than poor permutations.

The search also highlighted the study of Franklin, Waller, Pagliari, and Greene (2006) that reported on the development of a text-messaging support system dubbed 'Sweet Talk'. This text-messaging support study was subsequently enhanced by Middleton, Constantino, McGill, D'Souza, Twigg, Wu, …………and Wong (2021). This enhanced system was intended to improve self-efficacy, thereby facilitating the uptake of intensive insulin therapy to improve glycaemic control in paediatric patients with Type 1 diabetes. The study mentioned above sought to improve attendance at scheduled clinic visits through the use of daily text message reminders from the 'text-messaging support' software system. The study provided a breakthrough in e-health using reminder systems for adolescents with diabetes. The system enhanced self-efficacy and adherence by eliciting positive clinical and psychosocial outcomes. The authors recommended replication of the study for other chronic disease sufferers that require regular hospital visits and medicine taking. Similarly, Sotomayor, Hernandez, Malek, Parimi and Spanakis (2023) conducted a quantitative study to evaluate the feasibility of a telemedical system to improve control of the glycaemic index in adolescents with Type 1 diabetes mellitus. Their study used telemedicine to support patients via SMS advice that was given once a week. The study recommended technical support for the usage of self-management systems, and emphasized the role of moderating factors (age and attitude).

Both Middleton et al. (2021) and Sotomayor et al. (2023) acknowledged that changes to health behaviours are motivated by enhancing self-efficacy as explained by Social Cognitive Theory. However, the design of the text-messaging intervention failed to show how this behaviour could be integrated with technology to optimize self-management and control for diabetic patients.

Abbasinia, Ahmadi and Kazemnejad (2020) compared a two-way SMS cell phone messaging system with email reminders encouraging blood-glucose monitoring. Their study developed a web-based automated diabetes reminder system (CARDS) that generated messages that patients were required to respond to by sending in their blood glucose results. In addition to setting reminders on the secure CARDS website, patients were able to enter and review their blood glucose (BG) data. These authors observed that sustaining continuance usage of the reminder system was a challenge; hence the need for frequently renewed positive motivation to entrench behavioural change. In a rather different study Kraushaar and Bohnet-Joschko (2023) conducted a systematic review to investigate the prevalence and patterns of mobile device usage among physicians in clinical practice. The findings of their study revealed that there was increasing use of smartphones and medical apps in clinical practice, especially among junior physicians. However, they noted that most of the applications developed concentrated on communication and organization, documentation and monitoring, diagnostic and therapeutic decision support, and education. They recommended that healthcare organizations should systematically integrate mobile devices and apps into their knowledge management strategies and such systems should include modern ICT infrastructure and training courses. Further, they indicated that future studies should identify organizational and external factors that support efficient mobile device usage during clinical practice. This recommendation is aligned with the focus of this study although this study is patient-centred.

Alaslawi, Berrou, Al Hamid, Alhuwail and Aslanpour (2022) carried out a systematic review of factors affecting the adoption of apps by both patients and healthcare professionals. In their review searches were performed using PubMed, Scopus, CINAHL, Cochrane Central, ACM, and Xplore digital libraries for articles published between 2008 and 2020. These authors observed that in the majority of the articles reviewed, the studies had implemented a mobile phone healthcare application in addition to text messaging to improve self-efficacy and self-management behaviours without including behaviour triggers. Furthermore, they said that the reviewed studies lacked adequate sample sizes or durations of intervention to justify the findings regarding clinical and statistical significance. Alaslawi et al. (2022)

recommended that further studies be conducted to examine the perceptions of healthcare providers, the effects of the financial cost of using mobile phones by patients, and the environment of patients.

Alfaleh et al. (2023) examined the influence of technology usage on managing quality of life for children and families with diabetes. Their study was based on two technologies, an insulin pump and a continuous glucose monitoring system for the treatment of children with Type 1 and 2 diabetes. The results of their study indicate that technologies accessible via on the Web and a phone, play a great role in supporting diabetes self-management and, conceivably, quality of life. These researchers recommend further studies to investigate continuance usage, and the financial implications for patients using the technology. Although the studies of Alaslawi et al. (2022) and Alfaleh et al. (2023) were promising and identified factors needed for self-monitoring, their interventions lacked theoretical grounding. Dobson et al. (2017) emphasised that for the healthcare intervention to be successful, it must be theoretically based, contextualised by tailoring it according to the background and culture of the patients, as well as allowing individual choice to increase the sense of control of the patients.

Dobson, Whittaker, Jiang, Shepherd, Maddison, Carter, Cutfield, … Murphy (2016) implemented a text message-based diabetes self-management support system for patients with chronic diabetic conditions to reduce costs and complications risks. Their study indicates several factors that influence the self-management of diseases. These factors are self-efficacy and complexity of technology use, planned behaviours, diabetes distress, quality of life related to health, perceived social support, patient attitude and perceptions, financial costs, satisfaction and motivation, as well as the perceived usefulness of technology. These authors recommend further studies that contextualise chronic disease self-management, considering the cultural and social perspectives of the patients (Abbasinia et al., 2020). Their study was designed to develop protocols for the use of a self-management support system for blood glucose measurement. From the evaluation of the system they developed, they recommended that the text message-based intervention to support diabetic patients should integrate the aspects of behaviour management and technology, and be contextualised to individual patient's preferences and demographics. Hence, it should consider clinical characteristics as well as the culture and social-technical background of the patients. However, while their study identified several factors that were needed to inform the use of the text message-based diabetes self-management support system, it did not show how these factors could be integrated with technology to induce change in patient behaviour.

Dobson et al. (2017) conducted a cross-sectional survey to investigate the use of mHealth in delivering self-management support to young people with Type 1 diabetes. Their study emphasized the role of age in diabetes self-management. The study also indicated that mHealth has the potential to provide information and support to patients with chronic conditions. On the other hand, Duke, Barry, Wagner, Speight, Choudhary and Harris (2017) reviewed the effectiveness of distal technologies of several different systems. These included mHealth applications, social platforms, telehealth, game-based support, and patient portals to improve the management of Type 1 diabetes. Several factors that are critical for patients' self-management were identified by this study, namely, the privacy of patient data, ethics in the design and use of the self-management application, regulatory considerations and policies, issues of global technology adoption including technology characteristics, education or knowledge of patients of technology-related issues, and behaviour control. These authors recommended that further studies contextualize these factors to determine whether they were influenced by the patients' social-technical backgrounds and environment.

In their quantitative analysis of clinical trials using the text-message-based diabetes self-management support system that had been developed by Dobson et al. (2016), the Dobson et al. (2017) study increased the patients' sample size from that used earlier. However, their study only descriptively analysed the moderating factor, and this therefore limited their prediction of the continued use of the system by patients. Analysing the interacting effects of moderating factors is essential in predicting the continuance of usage of technology especially when other challenges, such as cost, time constraints and responsibilities increase (Tripathi & Shailja, 2018).

Analysing the interacting effects of moderating factors using multiple regression, like SEM, has been recommended in healthcare intervention research as a way to play a major role in predicting the future and continuance of usage of mobile technology (Abduo, Curtain & Othman; 2020; Reidy, Foster & Rogers, 2020).

Duke et al. (2017) reported several factors that influence patients' use of mHealth applications based on hypothetical adoption and use from work reported in the earlier literature rather than actual usage. Hence their interpretation of findings could have been limited due to hypothetical bias.

This current study counters any hypothetical bias by combining the review and identification of factors influencing mHealth self-monitoring usage with an analysis of the interacting effects of the moderating factors using SEM to predict future usage of the system.

Zhang, He, Shen, Yu, Pan, Zhu, Zhou and Bao (2019) carried out randomized controlled trials to investigate the effectiveness of smartphone app-based interactive management on glycaemic control for Chinese patients with poorly controlled diabetes. In their study they noted that smartphone apps are convenient, cheap and accessible globally, and that an interactive new type of self-management model needed to be leveraged for the control of chronic diseases. The findings of their quantitative analysis using multivariate linear regression indicated that app-based interactive management is effective in controlling glycaemic levels. These researchers recommended that, to achieve sustainability of app-based self-management, developers needed to combine self-management with interactive management, thus eliciting continued behavioural change and usability. Furthermore, their study recommended that future research should: extend features that allow real-time uploading of patient data; analyse the interacting effects of demographic factors of age and sex; and perform an evaluation of the long-term effects of a smartphone-based app on self-monitoring of diabetes. However, while their study highlights some factors that play a role in the usage of the mobile app interactive management system, the reported usage was in a controlled situation and the study lacked a theoretical foundation.

Larbi et al. (2019) conducted a systematic review and meta-analysis of studies published before 2015 on mHealth and online health diabetes intervention. Their study investigated the relevance of mHealth and online interventions that had been developed to address the needs of diabetic patients. Several aspects were revealed and categorized as: usability and the suitability of the mobile apps that had been developed and online interventions; effect on clinical health measures; data protection; information needs; other external factors; support and access to services; coping; patient engagement and empowerment needs; as well as technology needs. Among the issues identified were: contextualization and 'tailorability' (i.e., customisability); features and functions of the system; ease of use; challenges related to technology use by healthcare professionals and patients; suggestions for development and improvement; the feasibility of integration into healthcare practice; as well as user interface design; self-management; motivation; self-efficacy and autonomy; motivation; usage patterns and adherence; security and privacy; security policies; regulations and national standards; facilitating conditions; cost of use of mobile phones; risk assessment; education needs; and information availability.

Larbi et al. (2019) propose that in order to develop tools and services as well as to provide appropriate interventions for chronic diseases, there is need for further investigation and analysis of the factors in which both patients and their healthcare professionals play a major role. In addition, comprehensive methods are required to support the development and testing of contextualized models needed for healthcare interventions by factoring in the needs of specific patients, social and technical backgrounds, and cultures.

This current study answers this call by Larbi et al. (2019) by leveraging a triangulation of method of quantitative and Design Science approaches to develop a contextualized model of mHealth self-monitoring usage.

Reidy et al. (2020) based their work on the Behavioural Change Wheel (BCW) and the Theoretical Domains Framework (TDF) when investigating the effects of a facilitated web-based self-management tool for Type 1 diabetic patients using an insulin pump. Their study indicated that successful self-management systems are situational and contextual, with time and life circumstances being major moderating factors. These authors asserted that, during contextualization, several factors are considered, including social support, the environment, professional responsibility and risks. By using the BCW, TDF and the Capability, Opportunity, Motivation-Behaviour theories, their study confirms that all of the following play important roles in chronic diseases self-management: social influences, environmental context and resources, social or professional role and identity, beliefs about capabilities, optimism, intentions, beliefs about consequences, reinforcement, emotion, knowledge, cognitive and interpersonal skills, memory, attention, and decision processes, behaviour regulation as well as physical skills.

The study by Reidy et al. (2020) is considered to have made a breakthrough by combining a) the aspects of contextualization of the healthcare intervention model, b) the use of theory-driven intervention for self-monitoring of healthcare and c) the use of a large sample size of participating patients in the use of the mHealth system. A fragmentation or lack of integration of these aspects had been a limitation of several earlier studies (Dobson et al., 2016, 2017; Duke et al., 2017; Larbi et al., 2019). However, the Reidy et al. (2020) study did not consider the role of psychosocial support factors or their integration in the development of self-management models and systems. Integration of psychosocial support into routine diabetes care has been cited as important in reducing challenges of distress, anxiety, depression, sleep disorders, and likely risks of suicide (Joensen et al., 2019).

Abduo et al. (2020) conducted a quantitative cross-sectional survey in Kuwait to investigate the attitudes of patients toward the use of smartphone applications for diabetes management. The study established that even though smartphone applications are widely used for diabetic control, there are many barriers to their effective and continued use. These include lack of awareness, language barriers, cost of owning a mobile phone and buying data, readability of system messages, losing interest as time goes by, privacy concerns and mistrust, lack of time, as well as the complexity of navigating the system. The study by Abduo et al. (2020) acknowledges the importance of designing a reminder system and the relevance of analysing the moderating effects of the demographics of patients to determine their influence on continued usage. These authors recommended that future research be conducted on these aspects. However, while their study collected and analysed data quantitatively, it lacked a theoretical foundation and also did not show links between its measuring instrument and the literature of the study.

Lin et al. (2022) evaluated the accessibility and openness of patients with Type 1 diabetes to receiving mHealth support. Their study followed a descriptive analysis approach with data collected directly from patients with Type 1 diabetes. Although their study involved a large sample as had been recommended by previous studies (Dobson et al., 2016, 2017; Duke et al., 2017; Larbi et al., 2019), it only used descriptive analysis, and lacked the support of a theoretical background. Lin et al. (2022) recommended that, since mHealth already has a variety of digital tools and communication channels, future research should implement interactive voice response (IVR) rather than SMS for patients with the chronic diseases commonly occurring among the elderly. A study conducted by Umaefulam, Premkumar, and Koole (2022) examined the perceptions of indigenous women regarding the use of mHealth as a means of obtaining health information, and found that the perception of mHealth as a tool for delivering information depends on the delivery style, nature of messages delivered, and content delivered. This study observed that it is important to provide culturally appropriate support for chronic health conditions, particularly for those who must rely on self-management, as such can help prevent complications as well as morbidity. Furthermore, their study emphasized that mHealth is an effective tool for delivering health education across a variety of populations, and recommended contextualization of the healthcare interventions to the patient's culture and psychosocial backgrounds.

Researchers including Lin et al. (2022) and Umaefulam et al. (2022) have emphasized the importance of contextualization of mHealth interventions since an approach suitable for one population may not be appropriate for another. They stress that patients' views should inform the introduction of mHealth interventions for use in indigenous communities. Their studies also echo the call for bigger sample sizes during healthcare trials. However, even though they focused on the use of mHealth intervention rather than the development of systems or models, they lack a solid theoretical background. In addition, their studies did not analyse the interacting effects of the moderating factors to predict the continued use of the mHealth interventions.

Joschko (2023) conducted a systematic review of 25 studies on mHealth. Their study observed a significant improvement in healthcare care outcomes, such as compliance with medication taking when using SMS. According to the study, patients must have ongoing support from their healthcare providers to monitor and manage their diseases. The use of technology should be simple for patients to master, and they should feel confident in their abilities, recognise its value, and be positively motivated to use it.

The Kraushaar and Bohnet-Joschko (2023) review of using cell phone text messaging interventions to increase adherence, supported the findings of Abbasinia et al. (2020) by highlighting the need for behavioural change to improve health outcomes. Their studies recommended the use of models that support the integration of behaviour into technology usage for health interventions since adherence declines in adolescents due to competing demands of diabetes management, social and developmental needs.

Pi, Shi, Wang and Zhou (2023) conducted a meta-analysis of the effects of mobile phone intervention for self-management of diabetes through glycaemic control. The results indicate that mobile phone intervention is essential for significant improvement in glycaemic control and self-management. These researchers also reveal that technology supports knowledge acquisition and decision-making strategies. Volitional control, influenced by both motivational and action selection processes, is one of the major antecedents of self-management of chronic conditions. These authors recommended further investigation of the role of behaviour control and social and cultural aspects in studies of self-management of chronic conditions.

Amalindah et al. (2020) reviewed mobile intervention design in diabetes. Their study observed that, due to the near-ubiquitous presence of mobile phones, contextually relevant real-time help is easily available for self-management of diabetes. These researchers observed that mobile technology has the potential to provide the needed information to enable patients to take care of their lives themselves. Their study recommended further investigation of factors that influence patient adherence to treatment and participation, as well as the role of motivational strategies, skills, education and patient attitude toward technology.

2.6 Summary

Despite the increasing burden of chronic diseases such as diabetes, researchers have made progress in developing interventions at least to control, if not prevent the worst-case scenarios that could lead to high morbidity and mortality rates. Self-monitoring systems for mHealth have been developed as tools to improve awareness through information flow, as well as reminder systems for patients to adhere to prescriptions for medications. This chapter reviewed the literature relating to health and health systems in South Africa, and highlighted the challenges facing the health systems in developing countries in general and in South Africa in particular. The chapter discussed aspects of persuasive technology and the relationship between persuasive technology and behaviour. Furthermore, the chapter discussed existing mHealth self-monitoring systems and indicated their limitations and challenges.

The chapter further discussed work related to the current study by giving an analysis of reported findings on self-monitoring of chronic diseases. The discussion of related work revealed that for self-monitoring, behavioural change as well as contextualization are paramount. Contextualization has been emphasized by various researchers and understanding how indigenous populations engage with and use mHealth brings attention to the various factors that need to be considered when developing and implementing interventions.

This literature review revealed that some studies conducted to inform the mHealth intervention lacked theoretical background or used small sample sizes, while others used weak methods to report on the role of moderating factors. It confirms that most patients in developing and developed countries have access to mobile technologies and are receptive to receiving mHealth support to improve diabetes control. Hence, these patients are open to the use of smartphone apps to receive text messages as reminders for medicine taking.

The next chapter discusses theories related to technology adoption and use, as well as the interventions for change behaviour.

CHAPTER 3: THEORETICAL FOUNDATIONS

The previous chapter covered the literature on mHealth and persuasive technology and how the two can be integrated for use in the self-monitoring of chronic diseases. This chapter elaborates on the theoretical underpinnings of the study. First, the chapter sheds light on the Information Systems (IS) theoretical frameworks commonly used for studying social aspects of the acceptance and use of technology research. Secondly, the chapter discusses the behavioural change intervention theories that are relevant to healthcare self-management. For each theory discussed, the chapter gives its strengths and weaknesses, and highlights the constructs that were included in this study's conceptual model. Furthermore, the chapter presents the conceptual model that guided the flow of the study, including data collection and analysis.

3.1 Theoretical Overview

Persuasive design features of technological innovations, such as mobile applications, are intended to incentivize an individual to keep coming back; at the same time, they analyse the behaviour of the subject once connected (Fogg, 2009, 2020). Social media companies use the persuasive principle either by leveraging artificial-intelligence-embedded algorithms or psychological behaviour patterns that prompt an individual to make quick decisions (Asmah, Ofoeda & Agbozo, 2022). Hence, persuasive technology systems are designed to change the attitudes or behaviours of users through persuasion and social influence. This suggests that studies that embrace persuasive technology, such as the current one, should be underpinned by theories that explain factors that include individuals' behaviours and attitudes as well as social influence. In addition, they should include cultural perspectives, social norms and motivation as they play a catalytic role, and technology aspects, individual characteristics and perception of technology that include ease of use and usefulness (Larbi et al., 2019; Reidy et al., 2020).

3.2 Acceptance and Use of Technology Theories

The development of a mHealth self-monitoring model should be backed by theories of acceptance and use of technology with a strong emphasis on behaviour (Abbasinia et al., 2020; Duke et al., 2017; Middleton et al., 2021). It is essential to consider behavioural change in the development of mHealth self-monitoring since patients' behaviour may change during use as other factors become salient. Based on this understanding, the discussion of the following theories and models was considered relevant for this study.

3.2.1 Theory of Reasoned Action

The Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975; 1980) was developed to explain individuals' behaviour and how to acquire helpful behaviour routines. TRA constructs include behaviour, intention to perform the behaviour, attitudes, subjective norms and external variables. Subjective norms result from the social and environmental surroundings in which an individual is situated (Fishbein & Ajzen, 1980). Positive attitudes and subjective norms lead to better-perceived control in managing changes in one's behaviour, normally after motivation. This implies that the intention to accomplish a certain behaviour precedes the actual behaviour. TRA has been used extensively to explain the behaviour of individuals when performing a given act. The construct 'behavioural intention' in TRA has been widely used as a mediating factor in many subsequent theories and models to inform actual behaviour (Davis, Bagozzi, & Warshaw, 1989; Venkatesh, Morris, Davis & Davis, 2003).

In the case of this study, the TRA's constructs of behavioural intention, external factors such as social influence, and individuals' beliefs about mHealth self-monitoring systems were considered to be important and, therefore, these constructs were included in the conceptual model.

3.2.2 Theory of Planned Behaviour

One weakness identified is TRA's failure to account for individuals' perceptions of their agency or the power they have to decide how to behaviour; behaviour is ever under volitional control (Ajzen, 1988; 1991). Efforts to rectify this TRA omission have resulted in numerous extensions to TRA and the development of several other theories, among them the Theory of Planned Behaviour (TPB) (Ajzen, 1991). Notably, TRA also left out several important external variables and this has led to the development of many slightly different models and theories being used in today's Information Systems research (Davis et al., 1989; Venkatesh et al., 2003; Trafimow, 2009). One of the main differences between TPB and TRA is that the TPB offers a better understanding of individuals' actual attitudes that result in the physical behaviours being performed (Martin, 2017).

TPB links beliefs to behaviour and has three major constructs, namely attitude, subjective norms and perceived behaviour control. Based on the literature reviewed, TRA and TPB agree that individuals' behavioural intentions lead to actual behaviour. In a self-monitoring system, behavioural intention is imperative. According to Reidy et al. (2020), when a mHealth system persuades the patient, a behavioural intention is triggered and leads to an action. In this study, this refers to the patient's adherence to the medical personnel's prescribed medication regimen (Pourmand, Doshmangir, Ahmadi et al*.,* 2020).

Therefore, three constructs were selected from TPB and were included in the conceptual model of this study, namely attitude, subjective norms and behavioural intention. In conformity with previous research studies, attitude was categorized under individual characteristics, subjective norms under culture and beliefs, and behavioural intention acted as a mediating variable (Reidy et al., 2020; Abduo et al., 2020).

3.2.3 Social Cognitive Theory

Social Cognitive Theory (SCT) was developed to predict changes to individuals' behaviour based on an understanding of behaviour (Bandura, 1986). The theory examines personal factors and individual characteristics and the environment of the individual and how these affect behaviour. SCT postulates that individuals have beliefs and cognitive competencies that are developed and adapted to be compatible with their social influences and structures within the environment. With respect to this study, social influence was proposed to have good contributing and predictive value. SCT indicates that individuals tend to learn from others rather than only from their own experience (Bandura, 1986). This notion has made social influence a major antecedent in the theories of acceptance, adoption and use of technology (Venkatesh et al., 2003).

Therefore, the constructs of social influence, environmental factors, individual characteristics as well as behavioural intention were adapted to be used in the conceptual model.

3.2.4 The Unified Theory of Acceptance and Use of Technology

Self-monitoring using mHealth involves more than behaviour, hence related research should investigate the technology used as well as the support of the healthcare institution for the use of this technology. Venkatesh et al. (2003) believed that this support should be included under facilitating conditions and maintained that support is the core of user perceptions towards technology. The implication of this is that the chosen behavioural model should be combined with one or more models that explain the factors not included in the behaviour models. This led to the development of the

Unified Theory of Acceptance and Use Of Technology (UTAUT) and its subsequent modifications and extensions.

Venkatesh et al. (2003) developed UTAUT to unify eight models that had been previously developed to inform the acceptance and use of technology. The models aggregated in UTAUT include TRA, TPB, SCT, the Technology Acceptance Model (TAM), a combined theory of TPB and TAM, the Motivational Model, the Diffusion Of Innovations theory (DOI) and the Model of Personal Computer Use. UTAUT has a high level of predictive ability because it incorporates moderating factors and a variety of behavioural and non-behavioural factors. This has made it highly regarded, and it has been used in many research studies to explain the acceptance and use of technology.

The UTAUT's independent constructs (effort expectancy, performance expectancy, facilitating conditions and social influence) mediated by behavioural intention have been found to predict actual behaviour accurately (Venkatesh et al., 2012). This has motivated researchers to extend and modify UTAUT by adding more constructs (Kalema et al., 2014; Momani, 2020). In the development of UTAUT2, Venkatesh et al. (2012) introduced hedonic motivation, price value and habit to predict consumers' acceptance of technology. The independent constructs of UTAUT2 are moderated by the individual's demographics namely, gender, age and experience. UTAUT2 was found to have a higher predictive power than UTAUT and this has led to even more modifications and extensions. Researchers (such as, Momani (2020) and Taneja and Bharti (2021)), who have used UTAUT2 claim that the theory is more robust, trustworthy, and applicable to a wider range of technologies than UTAUT, especially after being modified or extended. Its moderating variables make it suitable for predicting the acceptance and use of innovations.

3.2.5 Technology acceptance and use theories: Strengths and weaknesses

A large number of theories and models have been developed to inform the acceptance and use of technology, and most of them have been as a result of extension or modification of the popular old models (TRA, DOI and TAM). These newer models concur that, much as there might be heterogenous factors leading to the success of a technological innovation, actual behaviour (acceptance or use of the innovation) is generally preceded by behavioural intention (Momani, 2020; Taneja & Bharti, 2021). The development of newer models and theories usually try to address the weaknesses of their predecessors. Table 3.1 presents a summary of the weaknesses and strengths of some commonly used models and theories for the acceptance and use of technology.

Table 3.1: Summary of Strengths and Weaknesses of Some Technology Acceptance and Use Models and Theories

Theory/ Model	Author	Origin	Strengths	Weakness
Theory of Reasoned Action (TRA)	Fishbein & Ajzen, 1975; 1980	Social Psychology	This is a vital theory in explaining human behaviour and is the basis of many theories explaining behaviour.	TRA assumes that behaviour is always under volitional control. It is limited in explaining other variables that influence behavioural intention such as mood, fear, anxiety, threat or previous experience.

Theory/ Model	Author	Origin	Strengths	Weakness
Motivational Model (MM)	Deci and Ryan, 1985	Information Technology	MM explains why motivation is crucial for users to change their beliefs and to elicit behaviour. Motivation is relevant in healthcare studies	MM concentrates on motivation and lacks many other factors to be purposefully adopted solely for use of acceptance and use of technology.
Social Cognitive Theory (SCT)	Bandura, 1986	Social Psychology	SCT is flexible in explaining the differences in an individual's behaviour. When there is a change in an individual's environment, personal behaviour may also change.	SCT assumes that there is automatic behavioural change when there are changes in the environment. The theory is based entirely on the dynamic interaction between an individual's behaviour and environment.
Theory of Planned Behaviour (TPB)	Ajzen, 1988; 1991	Social Psychology	TPB is applied to an understanding of an individual's account for the perceptions of the power they have over their behaviour.	TPB suggests that individual's behaviours are planned. It is limited in explaining other factors that influence behavioural intention.
Technology Acceptance Model (TAM)	Davis, 1989	Information Technology	This is a powerful model for technology applications. It has replaced TRA's attitude toward behaviour with two technology acceptance measures, perceived usefulness, and perceived ease of use. It is less general than TRA and TPB.	This model does not include the TRA's subjective norms construct. It does not provide feedback on factors such as integration, flexibility, completeness of information and information currency. It does not specify how expectancies are influencing the behaviour.
Model of PC Utilization (MPCU)	Thompson et al., 1991	Information Technology	MPCU presents a competing perspective to that proposed by TRA and TPB. As it explains voluntary usage, it concerns itself with actual behaviour rather than intention or predictive behaviour.	MPCU is limited to voluntary usage and pays no attention to mandatory usage.
Diffusion Of Innovations Theory (DOI)	Rogers, 1995	Social Psychology	DOI can explain various types of innovations. The DOI study was general rather than being specific to a particular technology. It explains and predicts the rates of the adoption factors of innovation.	DOI gives a scanty explanation of how individuals' attitudes lead to acceptance or rejection decisions. DOI concentrates on user perception of technology without explaining the characteristics of the technology itself.

Theory/ Model	Author	Origin	Strengths	Weakness
Decomposed Theory of Planned Behaviour (DTPB)	Taylor and Todd, 1995	Social Psychology	The theory expands on TPB by incorporating the DOI factors. Such expansion makes it more successful in explaining adoption and use.	The theory decomposes the constructs of TPB but asserts that there is prior planning of behaviours.
Combined model of TAM and TPB (C-TAMTPB)	Taylor and Todd, 1995	Information Technology	The combination of TAM and TPB enables this model to include new factors not only the behavioural factors explained in TPB.	Much as the theory is a combination of TAM and TPB, it does little to explain other factors that influence use, such as fear or threat.
Technology Acceptance Model-2 (TAM2)	Venkatesh and Davis, 2000	Information Technology	This model examines the influence of perceived usefulness and ease of use on social influence. The model's strength is seen in the inclusion of subjective norms as well as in explaining acceptance over time, based on users' experience with technology.	TAM2 is an extension of TAM and indicates that it should explain the influence of culture on users' behaviour.

Source: Fishbein & Ajzen, 1975; 1980; Ajzen, 1988; 1991; Bandura, 1986; Taylor and Todd, 1995; Davis, 1989; Venkatesh and Davis, 2000; Taylor and Todd, 1995; Thompson et al., 1991; Rogers, 1995; Deci and Ryan, 1985; Venkatesh et al., 2012; Momani, 2020; Taneja & Bharti, 2021

3.3 Behavioural Change Interventions Theories

Effective behavioural change interventions are essential in improving the design and implementation of evidence-based practice (Michie, van Stralen & West, 2011). To do this, interventions must be characterized appropriately and linked to an analysis of the targeted behaviour. The Medical Research Council evaluation framework (2000) to assess complex interventions in health services and public health practices, as well as in social policies that have important health implications, suggests that behavioural intervention theories can be used when conducting medical research (Skivington, Matthews, Simpson, Craig, Baird, Blazeby et al., 2021; Reidy et al., 2020). While there are various frameworks for behavioural change interventions, it is unclear how well they are working (Momani, 2020). A selected behavioural change theory to be used in a research should be well-aligned with the literature, and should indicate the design procedures that must be followed during the development of the intervention (Kwame & Petrucka, 2021).

Factors of the relevant behavioural intervention theory should help integrate psychosocial support into routine healthcare for patients with chronic diseases (Dobson et al., 2017; Skivington et al., 2021). These factors should be considered along with those that explain the perceptions of healthcare providers and patients about the use of technology (Umaefulam et al., 2022). In the absence of an understanding of the cultural and social environment of patients, together with behavioural and emotional factors, a self-monitoring system cannot offer effective intervention for chronic disease (Huzooree et al., 2019; Arsenijevic et al., 2020). Therefore, in order to design an effective patient-centred diabetes self-monitoring system, the model that informs the intervention design must consider the patient's behaviour and the factors that trigger motivation to use the system. Two theories namely, the Behavioural Change Wheel (BCW) and the theoretical domains framework (TDF), were considered relevant for this study.

3.3.1 The Behavioural Change Wheel

The BCW is a non-linear model developed by unifying 19 frameworks, nine intervention functions and seven policy categories for classifying behavioural change interventions (Michie et al., 2011). The model provides a comprehensive overview of interventions and policies and enables a systematic analysis of their selection. The BCW supports three major premises of capability, opportunity and motivation, also known as motivational behaviour (COM/COM-B). Capabilities refer to an individual’s psychological and physical ability to engage in an activity, including the knowledge and skills they possess. Motivation refers to the brain processes that energise and direct behaviour and opportunity refers to external factors that enable or prompt that behaviour (Reidy et al., 2020).

3.3.2 The Theoretical Domains Framework

The TDF is an integrative framework developed by Michie, Johnston, Abraham, Lawton, Parker and Walker (2005) from a synthesis of psychological theories to facilitate the understanding of behavioural change processes during the implementation of evidence-based interventions. The theory has been used when applying theoretical approaches to interventions aimed at changing behaviour (Cane, O'Connor & Michie, 2012). It is a useful conceptual basis for exploring implementation problems and designing interventions to enhance healthcare practice because it describes a wide range of potential mediators of behavioural change related to clinical actions. The fourteen domains of TDF have been widely used to study how behaviour changes when evidence-based care is implemented (Francis et al., 2012; Phillips, Marshall, Chaves, Jankelowitz et al., 2015).

Cane et al. (2012) validated TDF and aligned its 14 domains with COM-B to make it suitable for identifying behaviour determinants. These domains are social influences, environmental context and resources, social or professional role and identity, beliefs about capabilities, optimism, intentions, goals, beliefs about consequences, reinforcement, emotion, knowledge, cognitive and interpersonal skills, memory, attention and decision processes, behaviour regulation, and physical skills.

The alignment of TDF with COM-B has allowed the theory to be used in many studies implementing evidence-based healthcare (Bursey, Hall, Pike, Etchegary, Aubrey-Bassler, Patey, & Romme, 2022; Cowdell & Dyson 2019).

3.4 The Conceptual Model

As Michie et al. (2011) point out, policies can only influence behaviour through the interventions they enable or support. Therefore, it is crucial to place interventions between policies and behaviour. However, Venkatesh et al. (2003) observe that deciding which model to use to explain people's technology adoption behaviour can be challenging because it requires balancing theoretical parsimony with understanding. According to Bagozzi (1992), a model that is both parsimonious and has fewer constructs is preferred in such a situation. However, Venkatesh et al. (2003) were of the view that a detailed understanding of the phenomena being investigated is more important than parsimony. Taylor and Todd (1995) point to the importance of striking a balance between parsimony and contributing to understanding.

The effort to explain the behaviours of users towards technological innovations has attracted a wide variety of research, leading to the development of numerous theories, models and their extensions. Examples are TAM (Davis, 1989) and TAM2 (Venkatesh & Davis, 2000), UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2003). This has been while seeking to balance parsimony and content. The literature points to a lack of consensus in the selection of a suitable adoption model and this has made the process challenging (Venkatesh et al., 2003; Tarhini, Arachchilage, Masa'deh & Abbasi, 2015).

In line with the suggestion by Taylor and Todd (1995), balancing parsimony and the contribution to understanding in the development of a model of self-monitoring systems of mHealth, has led to the integration of constructs of behavioural change, technology, organisation, individual characteristics, social and cultural, as well as environmental aspects.

The literature reviewed revealed that the main factors that influence the use of mHealth self-monitoring systems by patients revolve around the acceptance and use of technology, a change in behaviour, the culture, and the patient's environment (Dobson et al., 2017; Kraushaar & Bohnet-Joschko, 2023; Larbi et al., 2019; Pi et al., 2023). These factors or similar ones have been confirmed in the technology acceptance and use theories as well as in behavioural intervention theories (Venkatesh et al., 2003, 2012; Cane et al., 2012; Phillips et al., 2015; Reidy et al., 2020). In addition, the literature pointed out the need to incorporate the demographics of users and the situational variables and to examine their interacting effects on usage.

To embrace these factors, and also to bridge the existing literature gaps, this study adopted the UTAUT2 (Venkatesh et al., 2012) as the underpinning theory. Furthermore, individual characteristics, culture, and mobile technology as endogenous mechanisms, together with exogenous mechanisms such as environmental aspects were introduced. Additionally, age, gender, experience and motivation were included as moderating factors. The conceptual model is illustrated in Figure 3.1.

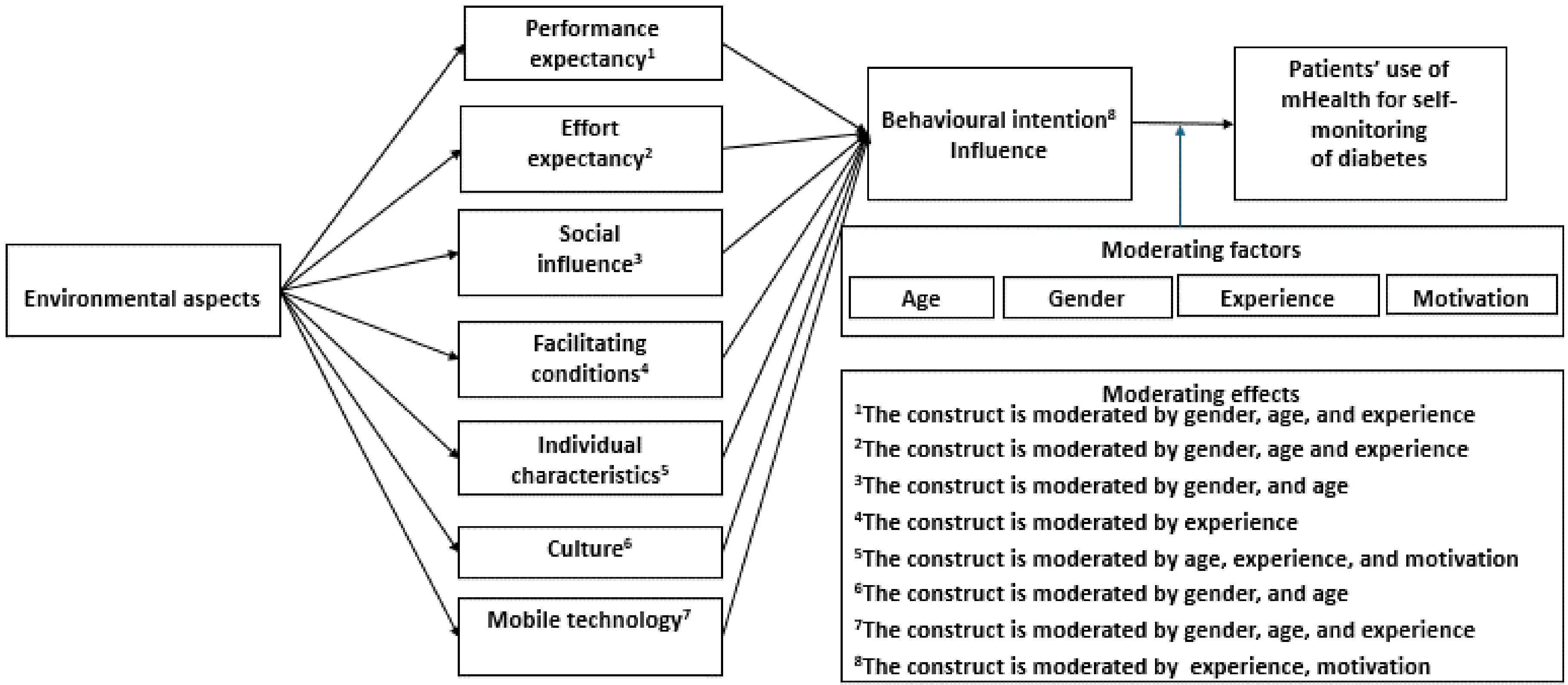


Figure 3.1: The Conceptual Model

3.4.1 Operationalization of the constructs

As demonstrated in Figure 3.1, the conceptual model presents eight independent variables, one mediating and dependent variable and four moderating factors. This section discusses each of these variables and how corresponding hypotheses were developed.

a) **Environmental aspects**: In this study, this construct refers to the surrounding factors in the patient's environment. These may include network availability, government policies and standards for the use of mHealth, affordability of the mHealth system by patients, availability of relevant infrastructure to support the use of the mHealth system, as well as educational support for people who do not know how to use mHealth systems (Cruz-Ramos; Alor-Hernández; Colombo-Mendoza et al., 2022). The environmental aspects have been known to influence the seven other independent variables of performance expectancy, effort expectancy, social influence, facilitating conditions, individual characteristics, culture, and mobile technology. Hypotheses **H1a – H1g** were developed from this understanding.

H1a: Environmental aspects influence the performance expectancy of patients required to use mHealth for self-monitoring of diabetes.

H1b: Environmental aspects influence the effort expectancy of patients required to use mHealth for self-monitoring of diabetes.

H1c: Environmental aspects influence the social influence of patients required to use mHealth for self-monitoring of diabetes**.**

H1d: Environmental aspects influence the facilitating conditions of patients required to use mHealth for self-monitoring of diabetes.

H1e: Environmental aspects influence the individual characteristics and attitudes of patients required to use mHealth for self-monitoring of diabetes**.**

H1f: Environmental aspects influence the individual characteristics and beliefs of patients required to use mHealth for self-monitoring of diabetes**.**

H1g: Environmental aspects influence the individual characteristics and skills of patients required to use mHealth for self-monitoring of diabetes**.**

H1h: Environmental aspects influence the culture of patients required to use mHealth for self-monitoring of diabetes**.**

H1i: Environmental aspects influence mobile technology use by patients adopting mHealth for self-monitoring of diabetes.

b) **Performance expectancy:** In this study, performance expectancy (referred to as perceived usefulness in TAM or relative advantage in DOI) is the degree to which patients believe that using self-monitoring mHealth systems will enable them to adhere to medicine prescription effectively and efficiently (Davis at al., 1989; Venkatesh et al., 2003). This construct embraces attributes such as usefulness in the daily life of patients, increasing the chances of patients being able to manage their lives well, and improving adherence to medication prescriptions. This study theorizes that performance expectancy is moderated by gender, age and experience, thus increasing its influence on the patients' use of self-monitoring via the mHealth system. The second hypothesis (**H2**) was developed from this understanding.

H2: Performance expectancy influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

c) **Effort expectancy:** The mHealth self-monitoring system, as with any other technology, can be perceived as either easy or difficult to use. Hence, effort expectancy could be seen as the degree to which patients perceive the mHealth self-monitoring system as either easy to use or as requiring little effort to use (Davis at al., 1989; Venkatesh et al., 2003). This construct has attributes that include the ease of use of mHealth, together with clarity and comprehension, and the ability to use the mHealth self-monitoring system. The influence of effort expectancy on the use of mHealth self-monitoring was moderated by gender, age and experience. The third hypothesis (**H3**) was developed from effort expectancy.

H3: Effort expectancy influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes

d) **Social influence:** This refers to a behaviour shared by a group of people who share the same norms and values as the patient (Venkatesh et al., 2003; Momani, 2020; Cruz-Ramos et al., 2022). This construct includes attributes such as closeness to other people who influence them, the desire to learn about what others do, and the willingness to learn from others. Social influence was proposed to be moderated by gender and age. This construct has led to the development of the fourth hypothesis (**H4**).

H4: Social influence influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

e) **Facilitating conditions:** In this study, facilitating conditions refer to support expected by patients from healthcare providers. Such support might be in terms of awareness of mHealth, training to use the service as well as the availability of the services (Venkatesh et al., 2003). The attributes of this construct include the availability of healthcare resources including human resources, health information, training, financial and technical support during usage. The fifth hypothesis (**H5**) was developed from this construct.

H5: Facilitating conditions influence the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

f) **Individual characteristics:** These refer to the non-technical factors individuals possess that enable them to participate in technological innovation adoption and usage (Momani, 2020). Individual characteristics are mainly influenced by cultural perspectives, beliefs, educational backgrounds, socio-technical background and socio-economic status. In terms of this study, this construct embraces attributes that include the patient's attitude towards the mHealth system, beliefs, skills to use mobile technology, and trust that allows the patient to be comfortable when using the mHealth self-monitoring system. Based on this understanding, hypotheses (**H6a-c**) were developed.

H6a: Individual's attitude influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

H6b: The individual's beliefs influence the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

H6c: The individual's skills influence the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

g) **Culture:** In this study, this construct combines aspects related to a patient's community, its values and norms, and its traditional or collective attitudes towards technology. It also embraces behaviours that influence an individual's life, as well as work that are directly linked to social influence (Trafimow, 2009). According to Jayeola et al. (2022), culture can either directly or indirectly influence a patient's attitude toward the acceptance and use of technology. The seventh hypothesis (**H7**) was developed from this construct.

H7: Culture influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

h) **Mobile technology:** This construct explains the mobile computing, medical sensors, and communications technologies for healthcare integrated into the design of the mHealth self-monitoring system. According to Goldfine, Lai, Lucey, Newcomb and Carreiro (2020), many wireless technologies can be used to monitor patients' health. The most widely-used technology is wearable sensors, which makes self-monitoring relatively easy, provides continuous feedback, and remains relatively non-invasive. Hence it plays a significant role in self-monitoring. The mobile technology construct embraces the mobile technology aspects of complexity, compatibility, scalability, motivation and persuasiveness. The eighth hypothesis (**H8**) was developed from this construct.

H8: Mobile technology influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.

i) **Behavioural intention:** To empower patients to self-monitor their health, healthcare interventions should be characterized appropriately and linked to an analysis of the targeted behaviour (Reidy et al., 2020; Skivington et al., 2021). Theories on the acceptance and use of technology agree that, for a behaviour to occur, an intention to behave in a particular way must first develop (Fishbein & Ajzen, 1975; 1980; Davis at al., 1989; Venkatesh et al., 2003, 2012). This has made behavioural intention a significant antecedent of the actual behaviour. Most theories and models that have been developed to inform technology acceptance and usage have been founded on the assumption that an individual's behaviour is preceded by positive intentions (Venkatesh et al., 2003, 2012; Momani, 2020; Cruz-Ramos et al., 2022). In this study, this implies that for patients to use the mHealth self-monitoring system, they have first to develop the intention of doing so (Fishbein & Ajzen, 1975; 1980). This understanding has led to the development of the ninth hypothesis **H9**.

H9: Behavioural intention has a directly positive influence on patients' use of mHealth for self-monitoring of diabetes.

3.4.2 Interacting effects of moderating factors

This study has suggested four moderating factors, namely, age, gender, experience and motivation. The acceptance and use of mHealth, like any other technology, largely depends on the patients perception of the system. However, these perceptions may change as time passes and the patients may stop using the system or their use of the system may reduce (Jayeola et al. (2022). For better prediction and also to allow continual usage it essential to measure the interacting effects of the moderating factors (Rahim, Humaidi, Aziz & Zain, 2022). The predictions of the interacting effects of the moderating factors are discussed below:

a) **Age:** It has been claimed that younger users tend to use technological innovations more than older ones do. Age has been found to have a moderating effect in many studies of technological innovation acceptance, adoption and use (Jayeola et al., 2022; Momani, 2020;

Venkatesh et al., 2003, 2012). For this study, age was predicated to have moderating effects on the influences of performance expectancy (PE), effort expectancy (EE), social influence (SI), individual characteristics (IC), culture (Cu) and mobile technology (MT) on behavioural intention. Hypothesis 10 (**H10**) was proposed based on this. However, on examining the interacting effects, a sub-hypothesis (moderating effects model) for each construct will be established.

H10: The patient's age has a moderating effect on the influence of PE, EE, SI, IC, Cu and MT on behavioural intention such that the moderating effect is higher for younger patients than for older ones.

b) **Gender**: Gender has also been proposed in various studies to have a moderating effect on independent variables and on behavioural intention's influence on actual behaviour of acceptance, adoption and use (Jayeola et al., 2022; Venkatesh et al., 2003, 2012). In this study, gender was predicted to have a moderating effect on PE, EE, SI, IC, Cu and MT's influence on behavioural intention to inform mHealth self-monitoring usage by patients. This understanding led to the development of the 11th hypothesis (**H11**).

H11: The patient's gender has a moderating effect on the influence of PE, EE, SI, IC, Cu and MT on behavioural intention such that the moderating effect is higher in males than in females.

c) **Experience**: Venkatesh et al. (2003, 2012) posit that individuals with more experience will find it easier to use new technological innovations than those with little or no experience. Experience was proposed to have interacting effects with the influence of PE, EE, IC, MT and facilitating conditions (FC) on the patients' behavioural intention (BI) to use self-monitoring mHealth. This led to the development of the 12th hypothesis (**H12**).

H12: The patient's experience has a moderating effect on the influence of PE, EE, FC, IC, Cu, and MT on BI and that of BI on mHealth self-monitoring usage, such that the moderating effects are higher in patients with experience than in those without.

d) Motivation: Both extrinsic and intrinsic motivation have been found to have strong effects on behavioural intention and actual usage of technology (Fishbein & Ajzen, 1980; Venkatesh et al., 2012; Sheng & Simpson, 2013). On the other hand, motivation has also been seen as a moderating factor that could speed up the influence of other variables on behavioural intention and behaviour. This study adopted motivation as a moderating factor with interacting effects on IC and BI and this led to the development of the 13th hypothesis (**H13**).

H13: Motivation has a moderating effect on the influence of IC on BI and that of BI on mHealth self-monitoring usage, such that the moderating effects are higher when patients are highly motivated than in those with low motivation.

As already explained, for all the moderating-factor hypotheses (H10 – H13), sub-hypotheses were deduced to represent each independent construct during testing. Hence each independent construct will be used.

3.5 Summary

Throughout the scientific research process, theoretical perspectives are essential when explaining observations about the causes or mechanisms of phenomena. The theoretical framework identifies key variables that influence the dependent variable, which is the phenomenon under investigation and examines how those variables may differ in different circumstances. Hence, hypotheses are tested to determine whether the independent variables influence the dependent variable, and if so, to what extent. Therefore, the use of theoretical frameworks and models provides researchers with a guide in the selection of research variables, an explanation supporting the formulation of hypotheses, and eventually an outline for the discussion of the findings. Furthermore, theories enable researchers to understand the connections between different studies. Therefore, this chapter discussed the theoretical foundations from which a conceptual model was developed. The constructs of the conceptual model have been operationalized, and the hypotheses developed for both independent and moderating variables. The next chapter discusses the methodology that was followed by this study.

CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

This chapter discusses the research design and methodology that were followed to achieve the goal and objectives of this study. First, the chapter sheds light on the research philosophy that outlines the paradigm and methods followed by this study. The chapter discusses the two phases this study followed namely, the traditional quantitative method, and the Design Science method that led to the development of the artifact.

4.1 The Philosophical Stance of this Study

Philosophy is a collection of principles, standards or beliefs used to explain an individual's behaviour and thoughts (Žukauskas, Vveinhardt & Andriukaitienė, 2018). Thus, research philosophy refers to the beliefs and thoughts of the researcher that underly knowledge about the research being carried out. The philosophy of the researcher is, therefore, the foundation on which the research should be designed, the paradigm to be used, the approach aligned with the paradigm, and thereafter, the research strategy, as well as data-collection methods and analysis (Tsung, 2016). The philosophical stance of this study was the belief that technology can play a key role in empowering diabetic patients to take care of their lives. The study believed that developing interventions, such as the mHealth self-monitoring system, offers opportunities to support the provision of flexible and accessible healthcare information to patients, thus enabling them to self-manage their health. To achieve this, this study integrated the factors needed for psychosocial support to change behaviour into routine diabetes care via mobile technology using an experimental design. Detailed procedures of how this was achieved are explained using the three characteristics of the paradigms that governed the flow of this study namely, ontology, epistemology, and methodology.

Tsung (2016) indicates that in social-sciences-related research, a researcher's philosophical understanding leads to three basic processes that help the smooth flow of research. These are demystification, informing and method-facilitation. Demystification refers to the researcher's ability to identify unsustainable assumptions, inconsistencies, and confusions that exist in a particular study domain based on the research findings. Informing, on the other hand, refers to the researcher being positioned in the domain of research that helps in weighing oneself in terms of the potentialities of what might be explored during research. Lastly, by method-facilitating the researcher selects suitable scientific methods to be used in the research. This makes a research philosophy of paramount importance to research (Žukauskas et al., 2018).

4.2 Research Design

Research is about generating new knowledge; hence, it involves defining and redefining a problem and setting the hypotheses by theorizing likely outcomes through the analysis of the collected data (Creswell & Creswell, 2018). This logical scientific process that is followed to conduct research is known as the research design (Yin, 2014). In other words, a research design is the overall plan the research follows to articulate and accurately put together all the components of the study, thus achieving the research goal, and ultimately solving the research problem. A research design helps the researcher to demonstrate the step-by-step processes followed when conducting research; providing information as to how the answers to the research question were obtained. According to Creswell and Creswell (2018), a research design should indicate and explain the following four steps:

- Identify the research problem through reviewing literature that is related to the study at hand.
- Specify and theorize related hypotheses or research questions that can be used as a basis for finding solutions to the identified research problem.
- Design the measuring instrument informed by the conceptual framework or model derived from the related literature and test the set hypotheses or answer the research questions.
- Analyse the collected data following an appropriate research approach to the study − a process essential for hypotheses testing or answering research questions.

This study followed a triangulation of methods in which quantitative and Design Science approaches were used. The study first reviewed related literature and that led to the design of the conceptual model on which the development of the measuring instrument was based. The measuring instrument was a close-ended questionnaire and was used to collect quantitative data. The data was analysed, and the findings were used to inform the design of the artifact as per the Design Science Methodology (DSM). DSM was followed because it covers all the activities necessary for delivering a mHealth self-monitoring model including reaching an understanding as to why the mHealth model should be developed, its feasibility, analysing the problem, providing the system design and architecture, and validating the model.

Based on the philosophical stance of this study, the reality was that diabetic patients, like any other patients with chronic conditions, do not adhere to the prescription of medications and, therefore, need a technological intervention (Kalema & Mosoma, 2019; Meier et al., 2020; WHO, 2020). On the other hand, the ontological perspective was that the problem could be solved both theoretically and practically. This led to the epistemological view of using DSR, since solving the problem requires a technology-based solution. This study was carried out in two phases. The first phase followed a quantitative approach in which data were collected and analysed to inform the development of the artifact. The second phase consisted of the design of an artifact for mHealth self-monitoring system based on the DSR approach.

4.3 Research Paradigm

Researchers need to follow proper guidelines to justify their findings. Future researchers can only replicate, extend or learn from a particular study if such a study has followed proper guidelines. Guidelines are known as the paradigm for the research (Lincoln, Lynham & Guba, 2018). Therefore, a research paradigm can be seen as a framework or collectively agreed-upon view of a subject that positions and dictates the direction of research (Yin, 2014). According to Lincoln et al. (2018), besides the recently added participatory paradigm, the four common paradigms used in research are the positivism, post-positivism, critical theory and constructivism. These have been combined and renamed in various research studies as the post-positivist (positivist) paradigm, transformative paradigm, interpretivist or constructivist paradigm, and the pragmatic paradigm (Creswell & Creswell, 2018). The choice of the paradigm to use in a research project is entirely dependent on the philosophical perspectives of the researcher. This might also be influenced by the researcher's own beliefs and perceptions, experience and background, as well as the beliefs of the study's adviser (Yin, 2014).

Researchers concur that the paradigm's characteristics namely the ontology (*What is reality?*), epistemology (*How is something known?*) and methodology (*How does one go about finding out the unknown?*), greatly influence a researcher's philosophical understanding, which later guides the flow of the research (Tsung, 2016; Lincoln et al., 2018; Žukauskas et al., 2018). These characteristics create a universally accepted standard of how a researcher views, discovers and uses knowledge. The paradigm characteristics are illustrated in Figure 4.1; and are discussed in the subsequent subsections in relation to this study.

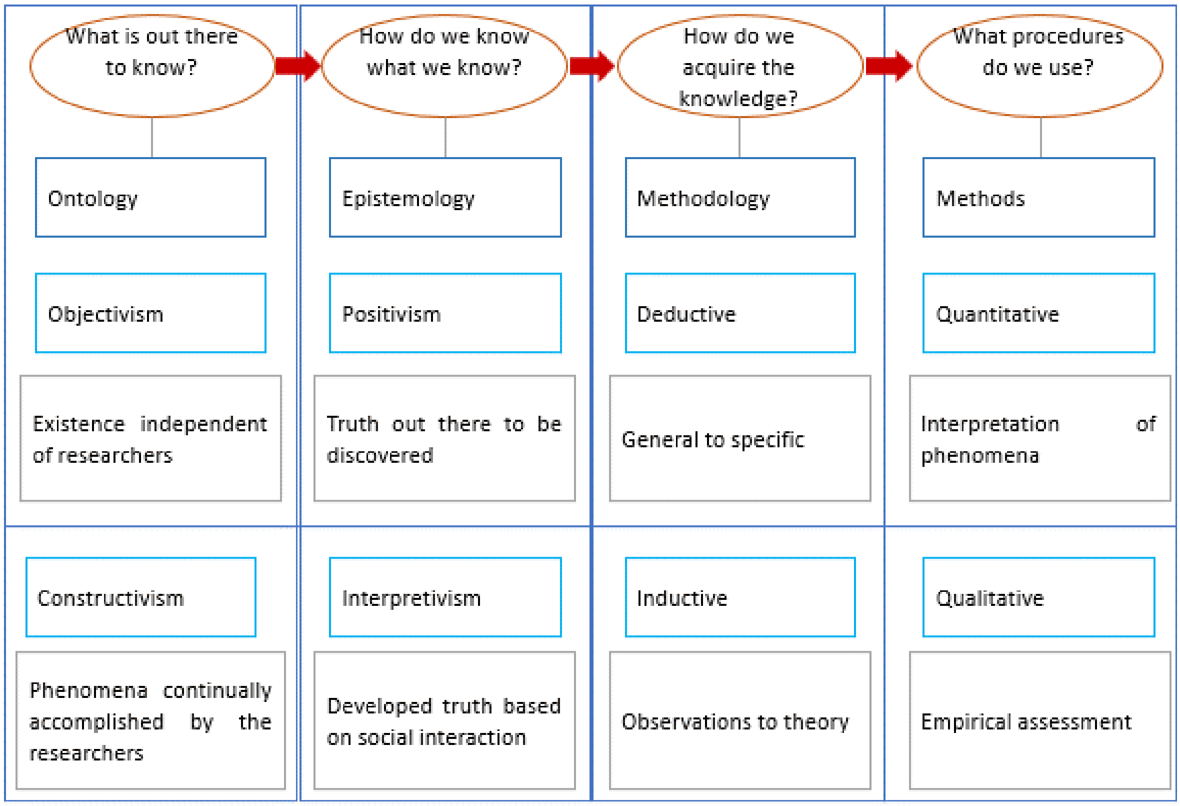


Figure 4.1: Classification of Paradigms (*Modified source: Lincoln et al., 2018*)

4.3.1 Ontology

Ontology is concerned with what is true or real, and the nature of reality. It signifies one's beliefs regarding the understanding of facts and how such facts can be interpreted and disseminated (Lincoln et al., 2018). Ontology clarifies the need to understand something by establishing the reality and what it entails. Žukauskas et al. (2018) state that ontology relates to the investigation of the observation of social entities, whether they are objective or subjective. These researchers further indicate that objectivism, on the one hand, is the ontological position that holds that the meaning of social existences are independent of the social actors. Subjectivism, on the other hand, is more related to interpretivism or constructivism perceptions of the social happenings and their relationships to the social actors.

In the case of this study, the reality is that many people in South Africa suffer from chronic diseases such as diabetes and these patients require routine taking of medications (Kalema & Mosoma, 2019; WHO, 2019). These patients must adhere to medical prescriptions if they are to reduce the effects of diabetes. However, lack of adherence, coupled with other challenges such as finance, long distance to medical facilities, as well as limited human medical resources, increases their chronic disease burden and to an extent, the mortality rate. This is the main reason for the need for a self-monitoring mHealth system that could trigger patient behaviour to adhere to drug prescriptions as given by medical personnel.

4.3.2 Epistemology

Epistemology relates to the nature of knowledge, its sources and the various methods of how such knowledge can be obtained (Lincoln et al., 2018). The epistemological understanding describes the nature, sources, possibilities, and limitations of knowledge in a given domain (Tsung, 2016). Therefore, epistemology is related to knowing reality by answering the questions *'How'* and *'What'* can we know? In this study, the epistemological stance was to give a clear understanding of precise methods that could be used to develop a mHealth self-monitoring system for patients with chronic diabetic conditions. In this study, it is believed that to develop such a system, a model must first be designed and quantitatively validated; only then can an artifact be used as a prototype for implementing an effective mHealth self-monitoring system. The selection of the quantitative approach led to the discussion of the methods that could be used for quantitative data collection.

4.3.3 Methodology

Methodology is defined as the process followed by a given research to establish knowledge and is based on an approach or strategy, as well as methods of data collection and analysis (Creswell & Creswell, 2018). Traditional scientific methodological approaches include quantitative, qualitative, and mixed methods, as well as DSM. In each of these, a researcher selects suitable strategies and techniques relevant to the study. This study followed a triangulation of method of both quantitative and Design Science approaches. The quantitative approach was leveraged to identify perceptions and their patterns that lead to behavioural change to take medicine. On the other hand, Design Science is concerned with the evolutionary ontology of both the problem and the artifact, implying that ontology combines the problem and the artifact (Purao, 2013). It is from this background that this study subscribed to the philosophy of pragmatism as an alternative to the philosophy of logical positivism. To design the artifact, both functional and non-functional requirements had to be established, and this was possible through quantitative data collection and analysis.

4.3.4 Research paradigm followed by this study

Since the philosophical perspective of this study was to use a positivist approach by combining both quantitative and Design Science methodologies, the research paradigm adopted was pragmatism. Hevner (2007) refers to pragmatism as a philosophy that believes that meaning and truth are both dependent upon practical effects and consequences. This accords with the Design Science approach that emphasizes the synergy between practical and theoretical contributions of research. Additionally, Deng and Ji (2018) confirm that pragmatism is the most appropriate and applicable underpinning philosophy for DSR, since DSR goes through different phases and can combine traditional interpretivism or positivism with experimental research. This implies that, through the lens of pragmatism, this study was allowed to use a combination of research paradigms, approaches, methods and techniques.

Hothersall (2019) notes that, as a paradigm, pragmatism offers an experience-based, action-oriented framework that helps researchers address issues both theoretically and practically. This study made use of an integrative approach to quantitative and Design Science methodologies that capitalised on and enhanced practice-based knowledge and research activities. The study sought to collect data from health workers in three South African provinces (KwaZulu Natal, Western Cape, and Gauteng) using a survey strategy by means of a close-ended questionnaire. Data was analysed using SEM, and the results were used as a basis for developing the artifact.

4.3.5 Research view of answering objectives of the study

Žukauskas et al. (2018) note that the use of a scientific research philosophy enables research to generate ideas which lead to knowledge in the context of the study that is being conducted. Additionally, Lincoln et al. (2018) indicate that the research philosophy and paradigm are characterized by a precise procedure consisting of several stages that inform how the research aims and objectives are to be achieved. Mackenzie and Knipe (2007) observe that, based on the paradigm of the study, the set research objectives and questions can be achieved by one or more methods, and may sometimes involve a combination of methods. Table 4.1 presents the methods that were used to achieve the set research objectives.

Table 4.1: Summary of Methods Used to Achieve the Research Objectives

Objective	Methods used	Chapter
The goal of this study was to develop a contextualized model for a persuasive technology mHealth self-monitoring system for diabetic patients in South African communities.	To achieve all objectives using the data analysis and implementation of the artifact.	Chapters 2, 3, 4, 5,6,7
Identify the challenges within the South African health system that prevent their healthcare teams from closely monitoring patients with chronic diseases such as diabetes.	Review of literature	Chapter 2
To identify the technological, psychological, individual, social, and external factors that influence patients' behaviours in interacting with technology.	Literature review and data analysis	Chapters 2, 3, 5 and 6
To discuss theories and models that could be used in the designing of persuasive technology mHealth monitoring systems for diabetic patients	Literature on theoretical foundations	Chapter 3
To use the Design Science methodological approach to incorporate persuasive technologies into a mobile application in developing an mHealth model to empower diabetic patients to monitor their health.	Implementation of the artifact	Chapters 4 and 7

4.4 Population and Sampling of Respondents

Many individual behaviours are attributed to personal traits and characteristics. However, it is possible that medical personnel and health workers can effectively and efficiently monitor the patients' daily routines and any deviations that might arise (Chifu, Pop, Demjen et al., 2022). As a result, healthcare providers may be able to identify functional and cognitive declines that affect their patients' daily activities (Abbasinia et al., 2020; GqaleniI & Mkhize, 2023). On the other hand, Chifu et al. (2022) advised that medical personnel can effectively use either probabilistic models such as the precision, recall and F-measure metrics, or wearable technologies for monitoring patients. Goldfine et al. (2020) strongly recommend the use of wearable technologies, as these provide real-time data and are user-friendly. From this understanding, the study population was only selected from the healthcare providers of the sampled provinces.

In this study, the researcher was interested in modelling the behaviour of diabetic patients with respect to their adherence to prescription medications. However, collecting data from patients was considered ethically inappropriate and was prevented by all the ethics clearance committees from which authorization was sought before data collection. Therefore, data was collected from healthcare providers, including medical personnel and social workers who meet these patients on a routine basis for counselling, medicine prescription, and treatment and these remained the only qualifying respondents of the study. This was similar to examples in the literature (Abbasinia et al., 2020; GqaleniI & Mkhize, 2023).

The annual indicator of trends in districts and provinces presented in the 2018/19 District Health Barometer (DHB) gives an overview of the prevalence of common disease burdens, and the delivery of selected healthcare services in the public health sector in South Africa (Massyn et al., 2020). A DHB is published annually and assesses the prevalence of diabetes as well as other diseases per province and in district municipalities based on the population of that province. This report reveals that the prevalence and coverage of treatment of diabetes varies widely across provinces. The 2018/19 report indicated that by 2017 diabetes among adults of 15 years and over was high in the Western Cape, KwaZulu-Natal, Eastern Cape, Free State, Northern Cape, Gauteng, Limpopo, Northwest and Mpumalanga. On the other hand, more treatment was dispensed in the Northern Cape, Western Cape, Free State, Limpopo, KwaZulu-Natal, Eastern Cape, Gauteng, Mpumalanga and Northwest (Massyn et al., 2020: 152). This report was used as the basis for selection of the geographical locations from which the respondents of the study were to be obtained.

4.4.1 Population of the study

To select the population of the study, the following three conditions were considered:

a) The first category was provinces with a high prevalence of diabetes but with insufficient treatment. Patients might therefore either lack awareness of treatment supplied, or the province lack sufficient facilities. These factors are covered by this study as those patients require self-monitoring. In this category, KwaZulu-Natal was selected as a geographical location of the population of the study.
b) The second category was a province with high prevalence and high treatment which implied that there was sufficient awareness and counselling. The Western Cape was selected as representative in this category.
c) The last category was proximity and with a relatively dense population and urbanization. The researcher was in a position to collect data for the study unhindered by too many hurdles. In this category, Gauteng and Mpumalanga provinces were selected.

The pre-exploratory study conducted in Gauteng and Northwest took place at the Tshwane District and Moses Kotane District municipal hospitals, and highlighted the fact that many South African district hospitals do not have specific diabetic clinics. Information gathered indicated that in these hospitals diabetic patients are treated along with other patients in the general wards or in outpatient clinics. This implied that all medical personnel and social workers were qualified to form the population of the study. It was also found that there are between 30 and 50 medical personnel and social workers at a district municipality hospital. Normally, there is one regional hospital in each province which is the major referral hospital. This study opted to use district hospitals in each selected province.

Massyn et al. (2020) state that the KwaZulu Natal province has 11 district municipalities, namely Amajuba, eThekwini, Harry Gwala, iLembe, King Cetshwayo, Ugum, uMgungundlovu, uMkhanyakude, uMzinyathi, uThukela and Zululand. Therefore, a minimal of 330 potential respondents is expected in that province. On the other hand, Western Cape has six municipalities namely, Cape Town, Cape Winelands, Central Karoo, Garden Route, Overberg and West Coast, implying that the province has 180 possible respondents. Gauteng has five district municipalities, namely the City of Ekurhuleni, Johannesburg, Sedibeng, Tshwane and West Rand, whereas the Mpumalanga province has three, namely, Nkangala, Ehlanzeni, and Gert Sibande. Hence three district hospitals from Gauteng and two from Mpumalanga were considered to provide services to five municipalities, with a probable population of 150 respondents. The total population of the study was 660 participants.

4.4.2 Sampling of the participants

By using the Krejcie and Morgan (1970) tool (illustrated in Table 4.2) to determine the sample size (s) for a finite population (N), this study established that for the population of 660 healthcare providers, a minimum sample size of 248 respondents was required. Based on the criterion that a respondent should either be a medical professional or a health worker, simple random sampling was used to select respondents. Depending on the sample size and the fact that the conceptual framework involved determining moderating effects, variance-based structural equation modelling (SEM) was considered appropriate for data analysis. Variance-based SEM using Smart partial least squares (SmartPLS) has the potential to analyse datasets smaller than 200 which is the required minimum for the traditional covariance-based SEM (Fan, Chen, Shirkey et al., 2016; Ringle et al., 2022). On the other hand, SmartPLS allows a simplified multivariate analysis approach for the data as well as supporting the use of variance-based SEM rather than a covariance-based approach that has limitations in fitting the model (Ringle et al., 2022).

Table 4.2: Krejcie & Morgan's (1970) Tool for Determining Samples Size(s) for Finite Population

Total	*Sample*	*Total*	*Sample*	*Total*	*Sample*
10 ⇒	10	220 ⇒	140	1200 ⇒	291
15 ⇒	14	230 ⇒	144	1300 ⇒	297
20 ⇒	19	240 ⇒	148	1400 ⇒	302
25 ⇒	24	250 ⇒	152	1500 ⇒	306
30 ⇒	28	260 ⇒	155	1600 ⇒	310
35 ⇒	32	270 ⇒	159	1700 ⇒	313
40 ⇒	36	280 ⇒	162	1800 ⇒	317
45 ⇒	40	290 ⇒	165	1900 ⇒	320
50 ⇒	44	300 ⇒	169	2000 ⇒	322
55 ⇒	48	320 ⇒	175	2200 ⇒	327
60 ⇒	52	340 ⇒	181	2400 ⇒	331
65 ⇒	56	360 ⇒	186	2600 ⇒	335
70 ⇒	59	380 ⇒	191	2800 ⇒	338
75 ⇒	63	400 ⇒	196	3000 ⇒	341
80 ⇒	66	420 ⇒	201	3500 ⇒	346
85 ⇒	70	440 ⇒	205	4000 ⇒	351
90 ⇒	73	460 ⇒	210	4500 ⇒	354
95 ⇒	76	480 ⇒	214	5000 ⇒	357
100 ⇒	80	500 ⇒	217	6000 ⇒	361
110 ⇒	86	550 ⇒	226	7000 ⇒	364
120 ⇒	92	600 ⇒	234	8000 ⇒	367
130 ⇒	97	650 ⇒	242	9000 ⇒	368
140 ⇒	103	700 ⇒	248	10000 ⇒	370
150 ⇒	108	750 ⇒	254	15000 ⇒	375
160 ⇒	113	800 ⇒	260	20000 ⇒	377
170 ⇒	118	850 ⇒	265	30000 ⇒	379
180 ⇒	123	900 ⇒	269	40000 ⇒	380
190 ⇒	127	950 ⇒	274	50000 ⇒	381
200 ⇒	132	1000 ⇒	278	75000 ⇒	382
210 ⇒	136	1100 ⇒	285	100000 ⇒	384

4.5 Data Collection Methods

Data for this study were collected from healthcare providers who are always busy and work with a large number of patients. Additionally, this study opted to follow a quantitative approach based on a survey strategy. Therefore, a questionnaire with close-ended questions was appropriate for data collection. The use of the questionnaire with close-ended questions allowed flexibility for healthcare personnel to complete the questionnaire in their free time, in addition to providing anonymity.

Based on the criterion for inclusion and after knowing that a sample size of 248 was needed for data collection, respondents were selected using simple random sampling. Simple random sampling is a type of probability sampling in which respondents are randomly selected to form a subset from the population of those qualified to participate in the study (Creswell & Creswell, 2018). With simple random sampling, each member of the population has an equal chance of being selected.

4.5.1 Questionnaire development

The conceptual model illustrated in Figure 3.1 has eight independent constructs, namely environmental aspects, performance expectancy, effort expectancy, social influence, facilitating conditions, individual characteristics, culture and mobile technology. The model had one mediating construct (behavioural intention), and one dependent construct (patients' use of self-monitoring systems for diabetes). Additionally, four moderating factors (age, gender, experience and motivation) were included in the model. The constructs and moderating factors were used to design the measuring instrument. The close-ended questions had a five-point Likert scale in which 1 and 5 represented strongly disagree and agree, respectively, 2 and 4 represented the respective intermediate values, and 3 represented neutral.

4.5.2 Questionnaire coding

For ease of analysis, the questionnaire constructs were coded as:

i. Environmental aspects: this construct was coded as Envt and its 5 attributes/ measuring items as Envt1 – Envt5.
ii. Performance expectancy was coded as PE, and its 3 attributes/measuring items as PE1 – PE3.
iii. Effort expectancy was coded as EE, and its 4 measuring items as EE1 – EE4.
iv. Social influence was coded as SI, and its 3 measuring items as SI1 – SI3.
v. Facilitating conditions was coded as FC, and its 3 measuring items as FC1 – FC3.
vi. Individual characteristics was coded as IndCh, and its 3 attributes − attitude as Attitude, beliefs as Beliefs, and skills as Skills.
vii. Culture was coded as Cu, and its 3 measuring items as Cu1 – Cu3.
viii. Mobile technology was coded as MT, and its 4 measuring items as MT1 – MT4.
ix. Behavioural intention was coded as BI, and its 3 measuring items as BI1 – BI3.
x. The patient's use of mHealth self-monitoring for diabetes was coded as mHealthSM, and its three measurement elements as mHealthSM 1 – mHealthSM 3.
xi. Moderating factors: age was coded as Age, gender as Gender, experience as Exp, and motivation as Motivation.

4.5.3 Advantages of using a questionnaire

Several advantages of using close-ended questionnaires have been documented. However, based on this study, using a close-ended questionnaire helped in the following ways:

- This study sought to collect data from medical personnel, a group of people indicated by a previous researcher to be ever busy. Using a closed-ended questionnaire was considered the most appropriate tool for data collection, as the intended respondents could complete it at their own pace and in their own time. Compared to having to make several trips to the medical facilities for the interviews, using a closed-ended questionnaire was not only time-saving for the respondents but also the researcher. In this case, the researcher distributed the questionnaires and collected them when the agreed time had elapsed. Giving respondents ample time to complete the questionnaire is essential in achieving a reasonable response rate.

- This study was conducted in two phases. The first phase followed the quantitative approach, developing a model for the mHealth self-monitoring system. The second phase was to use the developed model as the architecture on which the artifact design for mHealth self-monitoring was based. The researcher was working under a time constraint, hence using a close-ended questionnaire made the analysis of data relatively easy, cost-effective and time-saving.
- The development of the close-ended questionnaire followed the conceptual model that had been designed based on rigorous review of relevant literature. Hence, the measurement items of the questionnaire were based on the attributes of each construct, leading to the consistency of the questions asked. Such consistency in questioning, answering and analysis may be lost were interviews or open-ended questionnaires to be used.

4.6 Data Analysis

After coding, the questionnaire was transcribed into SPSS and exported to Smart-PLS for analysis. Preliminary findings of the study, such as the demographic and situational variables, were analysed using descriptive statistics. Thereafter, their interacting effects were analysed together with the constructs, using PLS-SEM. According to De Vaus (2014), depending on the software used for analysis a variety of methods and estimates may be used to prove the significance of independent variables as well as to test the suggested hypotheses. These approaches include parametric statistical techniques such as t-ratio, z-score, and critical ratio. Others are standard error approximations and T-statistics, paired with p-values.

This study used SmartPLS and applied T-statistics and p-values to prove significance and to test the hypotheses at a 0.05 level of significance (Ringle et al., 2022). According to Gardner and Altman (1986), for significance at 0.05, the T-statistics value should be greater than 1.96 and above 2.58 at 0.01. Hair, Sarstedt, Ringle and Mena (2012) assert that the use of variance-based SEM has been applauded for its enhanced features in determining the confirmatory tetrad analysis when empirically testing a construct's measurement model. These authors indicate that variance-based SEM also provides a flawless determination of impact-performance matrix analysis, as well as the response-based segmentation techniques that include finite mixture partial least squares (FIMIX-PLS). Ringle et al. (2022) confirm that covariance-based SEM is essential for giving simplified guidelines for analysing moderating effects, as well as determining non-linear effects and hierarchical components. The lack of statistical analysis of moderating effects has been a major limitation of many quantitative studies that analyse continuance usage and time-bound usage of technology.

Furthermore, the use of variance-based SEM commonly conducted using PLS-SEM affords sufficient control when maximizing the explained variance of the endogenous latent variables in an iterative sequence of ordinary least squares (OLS) regressions (Ringle, da Silva & Bido, 2014). Traditionally, the basis of estimating models via a series of OLS regressions reduces expectations of multivariate normality needed for maximum likelihood-based SEM estimations. The OLS and covariance-based SEM demands the use of a sample size of over 200 respondents (Hair et al., 2012). Furthermore, the use of covariance-based SEM requires the researcher to use other models for the analysis of moderating effects. This is not only cumbersome but also time-consuming (Ringle et al., 2022). After analysis, a final model was derived and based thereon the artifact was designed and evaluated.

4.6.1 Piloting the questionnaire

The questionnaire was pilot tested in two district hospitals, the Moses Kotane, and Tshwane municipal hospitals. Furthermore, a pilot study was conducted to test the feasibility of the main research survey, and also to determine the appropriateness of the measuring instrument to be used in the study. The purpose of the pilot study was also to assess the validity of the research techniques used in this investigation. In addition, the pilot survey allowed the researcher to determine the precision of the methods used in the investigation, as well as the replicability of the study (Yin, 2014; De Vaus, 2014). Other benefits of carrying out the pilot survey for this study include:

- Developing and testing the adequacy of research instruments. This was done to ensure that the closed-ended questionnaire used to collect data was free from semantic and syntax errors.
- The pilot survey also assisted in the assessment of the accurateness and workability of the research protocol, as well as the effectiveness of the sampling frame.
- During both the exploratory and pilot study, it was possible to assess the likely success of the proposed respondent recruitment approaches to be applied in the main survey.
- The pilot survey also assisted in the assessment of the effectiveness and appropriateness of the data analysis techniques decided on for the data from the main study. For this study, it was important to determine whether medical personnel could clearly articulate the patient's behaviour toward the prescription of medications. This was crucial for the development of the model and also for the artifact for the mHealth self-monitoring system that had to mimic the role of the medical personnel in reminding patients to take medicine.

4.6.2 Reliability and validity of the study

Based on the pilot survey results, it was possible to determine the consistency of the close-ended questionnaire items as well as their accuracy. De Vaus (2014) sees reliability as the extent to which the results obtained from the study can be reproduced when a similar study is conducted using the same questionnaire and conditions. De Vaus (2014) refers to validity as the extent to which the obtained study results were able to measure what was intended to be measured. In this study, reliability was statistically measured using the internal consistency check according to Cronbach's coefficients. Validity was achieved by checking the face, content, construct and criterion-related validities. As Yin (2014) indicates, validity can be established by checking how well the results corresponded to established theories and other measures of the same concept. Cohen, Manion, Morrison, and Morrison (2018) assert that it is important to assess both the reliability and validity of a study, in that a reliable measurement may not always be valid. These authors observe that reproducible results are not always correct, while valid measurements are generally accurate.

a) Reliability of the study

Reliability, also known as Cronbach's Alpha (α) was measured for the 11 constructs and sub-constructs of the measuring instrument namely, environmental aspects (Envt), performance expectation (PE), effort expectation (EE), social influence (SI), facilitation conditions (FC), individual characteristics (IndCh) that constituted three subconstructs of attitude (Att) beliefs (Beliefs) and skills (Skills). Other constructs of the measuring instrument were culture (Cu), mobile technology (MT), and behavioural intention (BI). The value of α was determined through several quality measurement items in a construct, their interrelatedness and homogeneity; and the results are as demonstrated in Table 4.3.

Table 4.3: Reliability of the Constructs

Constructs	Cronbach's Alpha (α)	α - Based on Standardized Items	Number of Items
Environmental aspects (Envt)	.707	.784	5
Performance expectancy (PE)	.687	.721	3
Effort expectancy (EE)	.624	.686	4
Social influence (SI)	.823	.857	3
Facilitating conditions (FC)	.751	.786	3
Individual char - Attitude (Att)	.588	.657	4
Individual char - Beliefs (Beliefs)	.685	.725	3
Individual char- Skills (Skills)	.703	.741	3
Cultural (Cu)	.576	.608	3
Mobile technology (MT)	.853	.874	4
Behavioural Intention (BI)	.765	.797	3

As illustrated in Table 4.3, performance expectancy (PE), effort expectancy (EE), individual char – attitude (Att) individual char – beliefs (Beliefs) and culture (Cu) had reliabilities (Cronbach's Alpha (α) scores) below the threshold of 0.7 but were above 0.5 and had fewer than four measuring elements. Hinton, McMurray and Brownlow (2014) say that constructs with Cronbach's Alpha values between 0.5 and 0.7 are moderately reliable and can be used for further analysis. Cronbach's Alpha may be affected by the length of the Lickert scale, the longer the scale, the more likely it is that its alpha will be higher. Hence, there would be a lower reliability coefficient for short-scale items because tau-equivalence would not be observed. The reliability of these 5 constructs was accepted as good as were interrelatedness and homogeneity and the constructs were included for further analysis (Tamilmani et al., 2021).

The rest of the constructs had reliabilities greater than the threshold (Heale & Twycross, 2015).

b) Validity of the study

As stated by Cohen et al. (2018), every study must ensure that the measuring instrument and the data it gathers fulfil all validity standards. Face validity, content validity, construct validity and criterion-related validity were all guaranteed for this study. These forms of validity were ensured by following the detailed steps below:

- **Face validity:** This form of validity was checked to ensure that the study's measuring instrument conforms to the common understanding and standards of research (Yin, 2014). In the case of this study, face validity was ensured by requesting experienced researchers to check whether the questionnaire conformed to the systematic sequential and logical flow as per constructs of the conceptual model. Also, during the pilot survey, the respondents were asked to report any ambiguity that could arise from grammatical and typographical errors, as well as from syntactical and semantic errors.
- **Content validity** was conducted to assess the degree to which the questionnaire items correctly represent the overall content of the research problem (Yin, 2014). This study used UTAUT2 as its underpinning theory and lens for data correction. Therefore, the study's

questionnaire items were compared to those of earlier researchers who had effectively validated their models using UTAUT2, including Venkatesh (2012), Tamilmani et al. (2021), Taneja & Bharti (2022).

- **Construct validity:** In the case of this study, the validity of the construct could be viewed as the conforming to a measuring instrument used in UTAUT2 and the knowledge of mHealth (Cohen et al., 2018). Hence, this form of validity test was conducted to ensure that the questionnaire measured the constructs of persuasive mHealth self-monitoring by including the technological and behavioural components.
- **Criterion validity:** For this study, the validity of the criterion refers to the degree to which the results obtained by this study correspond to other valid measures of mHealth (Cohen et al., 2018). This was conducted by carrying out and checking the interrelatedness of the constructs, using the correlation between the constructs.

4.6.3 Main survey

After all the grammatical and typographical errors in the questionnaire were corrected, and after ensuring its validity, the main data collection began. Data was collected from three provinces (KwaZulu-Natal, Mpumalanga and Gauteng). There were challenges to gaining access to the Western Cape Province. This could be attributed mainly to the fact that the researcher failed to find a contact person in the province to help make ethical clearance appointments with the provincial Health Department. The time constraint was another factor; for some provinces the researcher had to set appointments and make presentations to the Provincial Health Department Committee for ethics, an exercise that took much time.

Because this study had already secured ethical clearance in four districts, it was presumed to be sufficiently competent to make a good analysis. Besides, the study was not intended as a comparative analysis. Since all three provinces are distant from one another, it was imperative to get in contact with someone in each province for both practical and financial reasons. The role of the contact person was to assist in setting up appointments and for the distribution of questionnaires to and collection of completed questionnaires from the respective respondents. The distribution of the questionnaires, along with their response rate, is demonstrated in Table 4.4.

Table 4.4: Distribution of Questionnaire for Main Survey

Province	Questionnaires Distributed	Questionnaires Returned	Response Rate (%)
KwaZulu-Natal	150	127	84.6
Mpumalanga	100	72	72
Gauteng	100	58	58
Total	350	257	73.4

As demonstrated in Table 4.4 the response rate of 73.4% was considered good enough to continue with the analysis of data.

4.7 The Design Science Approach

The second phase of this study was conducted after model validation. The phase was based on DSM to develop the artifact since this methodology allows the theoretical and practical development of a real artifact for a specific problem domain (Hevner, 2007). The Design Science approach seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts. The paradigm denotes an inquiry-driven approach that provides specific guidance to research design procedures, and it is of importance in discipline-oriented research to create successful artifacts (Peffers, Tuunanen, Rothenberger & Chatterjee, 2007; Deng & Ji, 2018).

4.7.1 Steps followed during the Design Science Approach

According to Peffers et al. (2007), the Design Science process includes six steps, namely, problem identification and motivation, definition of the objectives for a solution, design and development, demonstration, evaluation and communication. The researchers noted that these steps are followed logically to come up with a fully-fledged artifact. In contrast, Deng and Ji (2018) argue that the DSR methodology is mainly constructive, starting with the identification of the problem and continuing right through to the description of the artifacts or their formal implementation. Hence its processes may vary depending on the nature of research. Therefore, DSM should value creative control and manipulation of the environment in addition to traditional research values such as seeking truth and understanding. This may require iteration of processes during the design and implementation of the artifact. This concurs with Vaishnavi and Kuechler (2015) who proposed that the researcher's ontological and epistemological viewpoints evolve as they progress through the DSR cycle, hence the need for iterations.

Carstensen and Bernhard (2019) note that in Information Systems, the six steps identified by Peffers et al. (2007) should be seen in the context of the three research cycles of the DSR perspective described by Hevner (2007). These cycles focus on relevance, design and rigor. The relevance cycle considers the need for research in three domains, namely, people, organizations and technical systems. An artifact is designed and evaluated during the design cycle, while the rigor cycle strives to achieve the comprehensive scientific knowledge needed to improve the knowledge base. In this study, activities including design, demonstration, evaluation, and communication were iterated, and contributed to the refinement of the artifact. The three research cycles of DSR are presented in Figure 4.2.

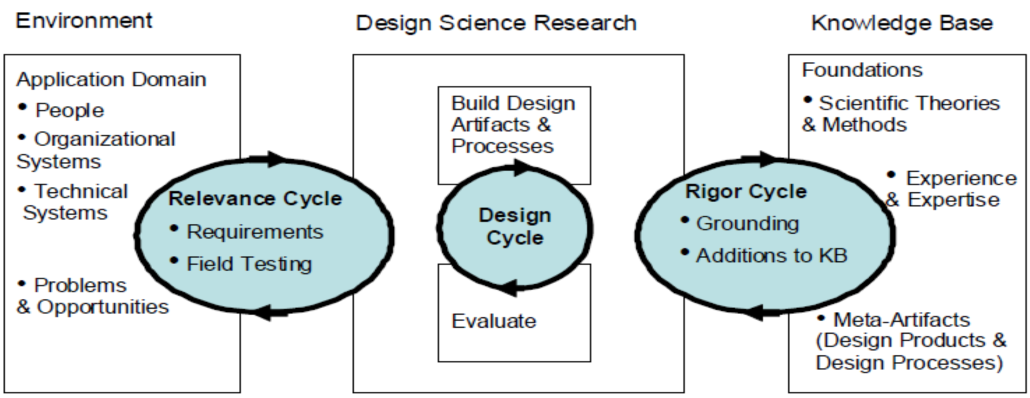


Figure 4.2: Design Science Research Cycles (*Source: Hevner, 2007*)

As shown in Figure 4.2, depending on the nature and goal of the research, different entry points exist where DSM could start in Information Systems research. However, Carstensen and Bernhard (2019) indicate that the entry points into DSM are more often predetermined by the intended output of the research. This argument supports the views of other researchers (for example, Gregor and Hevner (2013) and Deng and Ji (2018)) who indicated that there can be different outputs of DSR depending on the researcher's school of thought and the goal of the study. This study followed a pragmatic Design Science approach with the intended outcome being an artifact. Hence the most evident processes described in Chapter 7 start with the design and implementations through to communication. Other steps were covered in earlier chapters using the traditional quantitative approach.

4.7.2 Other DSR Process Model

Use of the Peffers et al. (2007) DSR process model has been popular in Information Systems studies. In this process model (see Figure 4.3), the DS sequence cycles through problem identification and motivation, objectives of solution, design and development, demonstration, evaluation and communication. The model allows several approaches and provides for different entry points into the process model depending on the type of development to be conducted. Information Systems researchers customarily follow the examples of behaviour research by using either a qualitative or a quantitative approach. In such situations the research will not necessarily need to go through all the phases, but might, for example, enter only at the design and development phase since other phases will have been explained in previously (Hevner, Comyn-Wattiau, Akoka, & Prat, 2019).

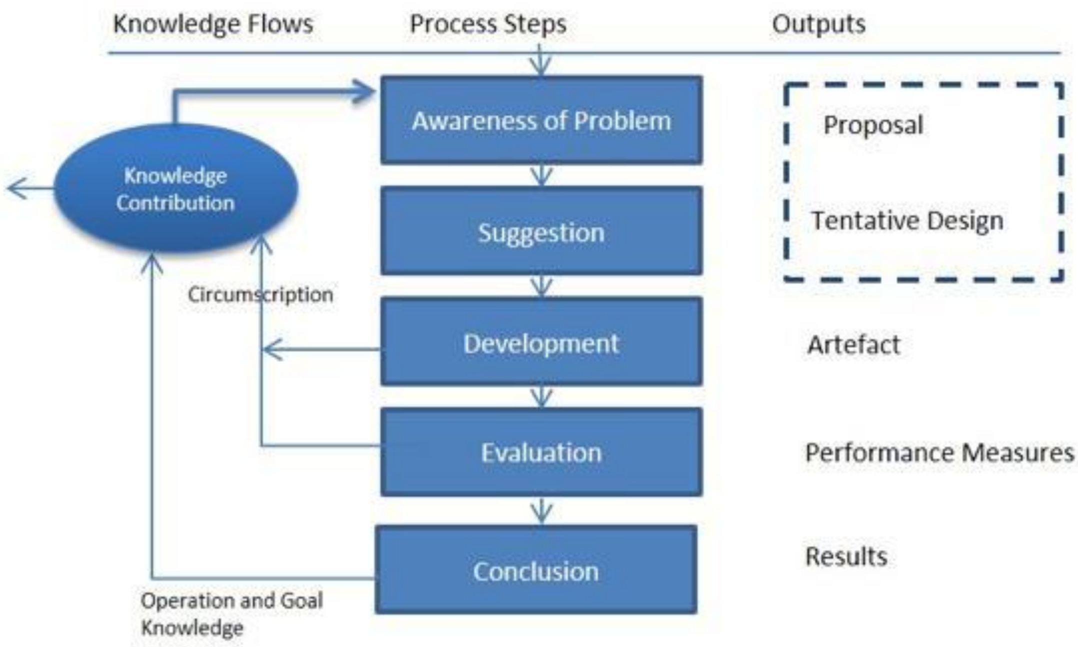


Figure 4.3: DSR Process Model *(Reproduced from Source: Peffers et al., 2007*)

Hevner et al. (2019) observe that IS research achieves the dual values of rigour and relevance. This explains why Information Systems research does not need to follow all the steps of the DS cycle in a prescribed way as it might require repetition of previous research. From the rigour side, the research acquires knowledge from the knowledge base, including existing theories, frameworks and reference to the existing Information Systems literature related to the research being conducted. In terms of relevance, the need arises for a new artefact, which is designed by following the experiment design approach and produces the artifact. This explains the approach followed by this study as the first two steps of problem identification and motivation as well as formulating objectives, as already explained in the chapters 1, 2 and 3 of the study, were based on the literature review and theory identification.

4.7.2 Design Science Guidelines in Information Systems

Gregor and Hevner (2013) elaborated on the nature of design research in the IS domain and provided a guide for reporting on and communicating DSR. Their work has been endorsed by IS researchers and has been widely used in many Information Systems studies using DSR (Deng & Ji, 2018). These guidelines are as follows.

Guideline 1- Design as an Artefact : Design Science Research must produce a viable artifact in the form of a construct, a model, a method or an instantiation.

Guideline 2 - Problem Relevance: The objective of Design Science Research is to develop technology-based solutions to important and relevant business problems.

Guideline 3 - Design Evaluation: The utility, quality and efficacy of a design artifact must be rigorously demonstrated via well-executed evaluation methods.

Guideline 4- Research Contributions: Effective Design Science Research must provide clear and verifiable contributions in the areas of the design artefact, design foundations or design methodologies.

Guideline 5- Research Rigour: Design Science Research relies upon the application of rigorous methods in both the construction and evaluation of the design artefact.

Guideline 6- Design as a Search Process: The search for an effective artefact requires utilising available means to reach the desired ends while satisfying laws in the problem environment.

Guideline 7- Communication of Research: Design Science IS Research must be presented effectively to both technology-oriented and management-oriented audiences.

4.7.3 Design Science Research Artifact

According to pragmatic design theory, artifacts are the outputs of design science, and these are classified into four types namely, constructs, models, methods and instantiations (Deng & Ji, 2018). From this, constructs are the conceptual units that describe problems within a domain and specify their solutions. On the other hand, models represent both problem situations and solution statements in Design Science activities by describing relationships among constructs. Models can be viewed as descriptions of how things are, but their concern is utility, not truth, which is the concern of theories. Methods are a set of steps used to perform a task. In general, methods are built based on underlying constructs and models. They are human-made artifacts that provide value insofar as they fulfil their purpose (Gregor & Hevner, 2013). Lastly, an instantiation is the realization of an artifact in its environment. The purpose of instantiations is to demonstrate and validate the feasibility and effectiveness of constructs, models and methods. There is also a possibility that an instantiation precedes the complete conceptualization of its methods, models and constructs (Carstensen & Bernhard, 2019).

This study followed the pragmatic design belief, and its targeted output was an artifact only, as demonstrated in Chapter 7. However, Gregor and Hevner (2013) emphasised that both the artifact and a theory are important knowledge contributions of DSR and are complementary rather than opposing perspectives. The artifact developed in Chapter 7 was informed by the validated model from the quantitative research as presented in Chapters 5 and 6.

4.7.4 The Design Process of the study's artifact

According to Peffers, Tuunanen and Niehaves (2018), DSM emphasises the design and construction of applicable artifacts (an application, system, method or other type of artifact). These authors indicate that the artifact should have the potential to make a contribution to the efficacy of IS either in organisations or in a community. Additionally, according to Deng and Ji (2018), in IS the design process of the artifact could follow any of a variety of processes, and it may be the activity that is least concerned with rigour. However, the designed artifact should have the following characteristics. Abstraction - it must be applicable to a class of problems. Originality - it must substantially contribute to the advancement of the body of knowledge. Justification - it must be justifiable in a comprehensible manner and must allow for its validation. Be beneficial - it must yield benefits, either immediately or in the future, for the intended group or community.

The intended artifact for this study was a mHealth self-monitoring system for patients with diabetic conditions. The system design is demonstrated in Chapter 7 and was achieved based on a mobile application development platform. The system was designed as a reminder to patients to adhere to the medical prescription provided to them by a medical professional person as non-adherence has been cited as a challenge with many patients suffering from chronic conditions (Meier et al., 2020). The design of the mHealth self-monitoring system, the artifact, followed a rigorous process. Its architecture was informed by the model validated in the quantitative phase (Phase 1) of this study. The actual development followed the iterative process recommended in software engineering where both functional and non-functional requirements were compared to the needed characteristics of the artifact (Peffers et al., 2018; Ushakova, Skorin & Shcherbakov, 2021). Finally, the artifact was evaluated descriptively using data collected from experts that were given access to the system, used it and then were asked to report on its functionality. This was as recommended for DSR artifacts and also in the software engineering testing of a system (Peffers et al., 2018; Ushakova et al., 2021; Venable, Pries-Heje & Baskerville, 2016).

4.7.5 Evaluation of the artifact

Researchers (for example, Peffers et al. (2018) and Venable et al. (2016)) have emphasized the importance of DSR artifacts and have developed guidelines and frameworks that could be used by researchers during the evaluation process. The frameworks are a set of parameters that can be tested during evaluation of the associated frameworks. Seven evaluation patterns are recommended, demonetarisation or completeness, performance or usability, effectiveness, absoluteness or reliability, ease of use, usefulness and complexity analysis or navigation. Specifically, regarding the use of DSR in IS research, if the developed artifact is a system or an application, its evaluation should be in line with the identified non-functional and technical requirements of the system (Elragal & Haddara, 2019; Hevner et al., 2019). Hence, parameters of completeness, performance or usability, effectiveness, absoluteness or reliability, ease of use, usefulness and complexity analysis or navigation are appropriate to the evaluation of such an artifact (Elragal & Haddara, 2019; Hevner et al., 2019).

A complementary view is offered by Deng and Ji (2018), who noted that the evaluation of the artifact in IS research should focus on the intended use and the context in which it will operate. Hence, it should match the intended design outcomes as well as consider the style of the artifacts. The evaluation of a DSR artifact should include the long-term organizational impact and the societal impact (Deng & Ji, 2018). Hence, evaluating for completeness, performance, and usefulness are paramount. This study developed a mHealth self-monitoring system to be used by chronic diabetic patients. Therefore, the parameters that were included in the evaluation were completeness, functionality, accuracy, usefulness, consistency, performance and usability.

4.8 Ethical Considerations

As this was a healthcare-related study, ethics clearance was sought from both UNISA and regional health departments that had been identified for data collection. According to Babbie (2016), social science research is conducted within the boundaries of the political codes and systems of the societies that are being investigated and these codes are known as research ethics. Babbie (2016) further notes that there are five ethical processes that a research study should follow. These are obtaining informed consent, minimising the risk of harm during research, protecting the confidentiality and anonymity of the participants, avoiding deceptive practices, and providing the right to withdraw. This study was also guided by the standards and procedures of the UNISA ethics committee, as well as the COVID-19 standards, to ensure that no harm was inflicted on the study participants. In addition, ethics standards guided the handling of data during collection and analysis. Ethical standards and procedures, as well as the approval letters, are attached as appendices to this thesis report.

As alluded to by Babbie (2016), ethical processes were followed in the administration of a survey using a questionnaire. The questionnaire was accompanied by informed consent forms and a cover letter explaining aspects related to informed consent of the respondents. This minimised risks to the respondents, their rights and privacy issues as well as anonymity, expected benefits from the investigation, and participation voluntariness in the study. These aspects are explained in the following subsections.

4.8.1 Respondents' informed consent

The UNISA standard informed consent forms were prepared and accompanied the questionnaire in the data collection process. During the pre-data-collection visits, the informed consent documents were read aloud and explained to the respondents. Respondents were also asked to read these documents independently before agreeing to participate in the study. The informed consent leaflets explained in detail the purpose of conducting the study, the voluntariness of participation, as well as the participants' rights to withdraw from the study at any point should they feel displeased by the questions. Because this study only dealt with medical personnel and healthcare workers, all respondents were literate and therefore understanding the implication of informed consent was not perceived as a challenge.

4.8.2 Minimizing the risks to the respondents

This study was concerned with collecting data relating to patient behaviour toward taking medicine as prescribed by medical personnel. The questionnaire items related to how the medical personnel or healthcare workers view these behaviours. Therefore, the study did not anticipate harm or discomfort to either the respondents or to their patients. The same message was conveyed to the respondents in the cover letter and in the informed consent leaflets that accompanied the questionnaires. To ensure anonymity, respondents were requested not to include any form of identification on the questionnaire (such as names, cell phone numbers, email addresses or staff numbers). This was to ensure that participants were aware that the study was not associated with any direct or indirect risk. Nothing was likely to be associated with them individually or with their organizations.

4.8.3 Confidentiality, anonymity, rights and privacy

The guarantee of confidentiality and anonymity are significant factors that respondents to the study should be assured of (Babbie, 2016). In the case of this study, respondents were guaranteed that all responses obtained from the questionnaires would remain anonymous. To ensure that this requirement was met, the questionnaire did not ask respondents for their contact details or any form of identification. Furthermore, the completed questionnaires were collected in a sealed box positioned in the staff rooms. Respondents were cautioned against scanning and emailing completed questionnaires to either the contact person or the researcher. Consequently, during data analysis, the findings of the study were reported as a whole, without comparison between the different provinces or district municipalities where data was collected.

4.8.4 Ensuring that permission is obtained

The UNISA ethics approval process reminds a candidate to obtain permission before collecting data. Provincial health departments request that candidates who wish to collect data from their staff obtain permission from their own ethics committees before the data collection process is allowed. These two conditions were met; permission was obtained from each province in which data were collected. The permission letters from the respective provinces are appended to this thesis.

4.9 Summary

This chapter discussed the methodology that was followed by this study. The discussion embraced the two research approaches that were used (quantitative and Design Science). Since DSR aims to create innovative solutions to real-world problems through the use of design principles and methods, the six steps of DSR were highlighted and for each step the methods used were discussed. Care was taken to ensure that suitable research methods, approaches and designs aligned with the research objectives were followed for each approach. By understanding and applying the appropriate research methodology in DSR, this study not only contributes to the advancement of knowledge but also to the development of a practical solution, the mHealth self-monitoring system, which was intended to solve the challenge of medical adherence.

By using portable technological devices, patients can monitor their health status and also follow treatment regimens without visiting the clinic. Remote patient self-monitoring not only improves the lives of patients but also enables medical personnel to adjust medication doses or treatment regularly to improve outcomes. This chapter discussed the processes and procedures followed to design the mHealth self-monitoring system. The chapter details how the quantitative approach was followed in collecting data used to test and validate the conceptual model. This led to the development of the mHealth self-monitoring artifact.

CHAPTER 5: DATA ANALYSIS AND PRESENTATION OF RESULTS

This chapter presents the results of this study. The chapter begins by presenting the data cleaning process also known as data screening. Data screening is followed by a presentation of the frequency of the demographic and situation variables of the respondents. The chapter then presents the factor loadings and the average variance extracted (AVE) that was used to determine the discriminant validity. Next the chapter presents the measurement model and its fitness indices. After elaborating on the measurement fitness, the chapter discusses the structural model on which the testing of the suggested hypotheses was based for both the constructs and the moderating variables.

5.1 Data Screening

After collecting the completed questionnaires, data screening or cleaning was carried out. Initial screening was conducted by the researcher to assess whether all sections of the returned questionnaires had been completed by the respondents. Those questionnaires with missing data were discarded. Of the returned 257 completed questionnaires, 33 were found to have missing data and were discarded. The 224 complete questionnaires were then transcribed into SPSS for further analysis. As this study intended to use SEM, the dataset that had been transcribed was screened for multivariate assumptions. Doing this ensured conformity allowing confirmatory factor analysis and the model structural testing to be conducted effectively (Hair et al., 2006). The Mahalanobis distance was used as this is the standard test for outliers in the normal distribution data. Figure 5.1 illustrates the normal probability plot (P-P plot) graph that was obtained to assess multivariate normality for the dependent variable mHealthSM with 158 questionnaires finally retained (N = 158).

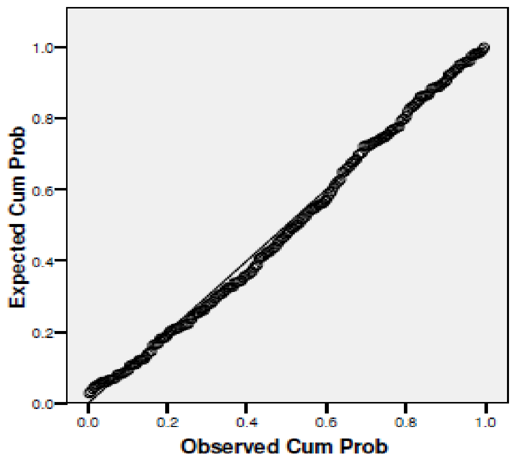


Figure 5.1: Normal P-P Plot of Regression Standardized Residual

The graph (see Figure 5.1) represents the normal P-P plot of the regression standardised residual. After numerous data screening and cleaning attempts, outliers were eliminated; the final data set to be used for analysis contained data from 158 respondents. In the plot the graph is not curved and is as expected which implies that there are few to no outlier data sets that need further elimination. Tabachnick and Fidell (2013) note that the residual scatter plot tests for normality, linearity and homoscedasticity between the dependent variable, namely the mHealthSM score, and errors of predictions.

Figure 5.1 indicates that, after eliminating outliers, the number of residuals has been reduced, and are in a straight-line alongside the dependent variable that is intended to be predicted; this suggests linearity. The P-P plot graph also indicates that the distances are nearly equal rather than sparse, which suggests the existence of homoscedasticity. The results demonstrated in Figure 5.1 confirm that the cleaned data were fit for SEM (Hinton et al., 2014). However, since after data screening a number of outlier data sets were discarded, a smaller sample size remained and this was less than the recommended minimum for confirmatory factor analysis (CFA) using covariance-based SEM (Hair, Black, Babin, Anderson, & Tatham, 2006). As a result, the subsequent data analysis had to be carried out using variance-based SEM via Smart-PLS (Ringle et al., 2022).

5.2 Frequencies of the Demographics and Situational Variables

This section presents the descriptive analysis of moderating and situational variables. Five variables namely, age, gender, experience, awareness and motivation were assessed. Results presented in Table 5.1 demonstrate the frequencies of these variables.

Table 5.1: Frequencies of the Moderating Variables

Variable	Items	Frequency	Percent	Validity Percent	Cumulative Percent	Variable
Awareness	Valid	Yes	108	68.4	68.8	68.8
		No	48	31.0	31.2	100.0
		Total	157	99.4	100.0	
	Missing	System	1	0.6		
	Total		158	100.0		
Motivation	Valid	Low	107	67.7	68.2	68.2
		High	44	27.8	28.0	96.2
		3	6	3.8	3.8	100.0
		Total	157	99.4	100.0	
	Missing	System	1	0.6		
	Total		158	100.0		
Gender	Valid	Male	18	11.4	36.7	36.7
		Female	31	19.6	63.3	100.0
		Total	49	31.0	100.0	
	Missing	System	109	69.0		
	Total		158	100.0		

Variable	Items	Frequency	Percent	Validity Percent	Cumulative Percent	Variable
Age (years)	Valid	21 - 30	25	15.8	15.9	15.9
		31 - 40	25	15.8	15.9	31.8
		≥ 41	107	67.7	68.2	100.0
		Total	157	99.4	100.0	
	Missing	System	1	0.6		
	Total		158	100.0		
Experience (years)	Valid	0 – 5	36	22.8	22.9	22.9
		6 – 10	13	8.2	8.3	31.2
		≥11	108	68.4	68.8	100.0
		Total	157	99.4	100.0	
	Missing System		1	0.6		
	Total		158	100.0		

Several researchers have indicated the importance of analysing moderating variables for descriptive and interacting effects. These researchers argue that because individual behaviour and perception can vary over time, the analysis of moderating variables gives a good prediction level, thereby enhancing the validity of the findings (Venkatesh et al., 201; Tripathi & Shailja, 2018). As shown in Table 5.1, for unknown reasons the majority of the respondents (n= 109) did not disclose their gender, although only one respondent did not disclose their age. From the findings, the majority of respondents 67.7% (n= 107) were above the age of 40 years. In most cases, older medical personnel have been working for a longer period. These people have good experience and have interacted with a variety of patients; hence they are in a good position to give valid answers relating to patient behaviour towards medical prescriptions.

The results also indicated that 68.4% (n=108) of the respondents had more than ten years of experience. These findings concur with those of Tripathi and Shailja (2018), who considered that there is a complementarity between existing human capital and behavioural change. The authors stated that the situation is not only noted in technology adoption and use, but is also found when individuals are working with one another, experience being essential for better judgment and decision-making. This implies that the good experience the study respondents would led to a certain level of validity of the findings. The experience of the respondents is also demonstrated graphically in Figure 5.2.

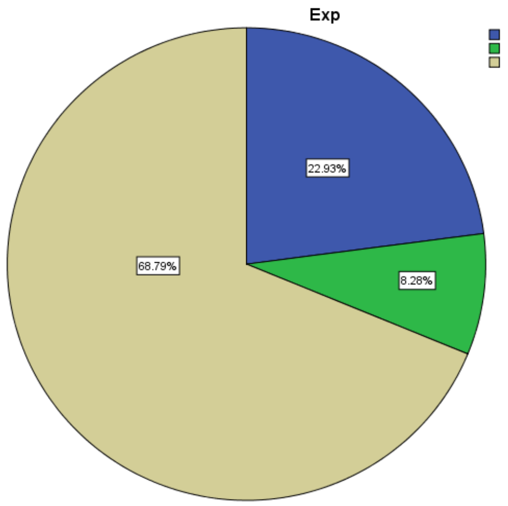


Figure 5.2: Experience of Respondents

Respondents were asked whether patients were aware that they could communicate with medical personnel electronically using SMS, WhatsApp, emails and direct cell phone calls. The results indicate that many respondents 68.4% (n=108) answered in the affirmative. This implies that patients could indeed utilise the functionality of collaboration and social networking in the self-monitoring system developed. Similarly, the majority of 67.7% (n=107) of respondents agreed that the awareness of patients leads to their motivation to use technology to communicate with medical personnel. These findings concurred with what Fogg (2020) suggested, that persuasiveness to enlist behavioural change needs motivation, and is therefore a major antecedent. This also implies that since the self-monitoring system of mHealth is based on behavioural change, as a moderating factor motivation plays an essential role encouraging patients to adhere to the prescription of medications,. Motivation as a moderating factor is imperative for patients' change of beliefs that elicit behaviour to positively respond to interventions, as triggered by a self-monitoring system (Deci & Ryan, 1985; Sheng & Simpson, 2013; Phillips et al., 2015; Reidy et al., 2020). The motivation of reported patients to use technology to contact medical personnel is shown graphically in Figure 5.3.

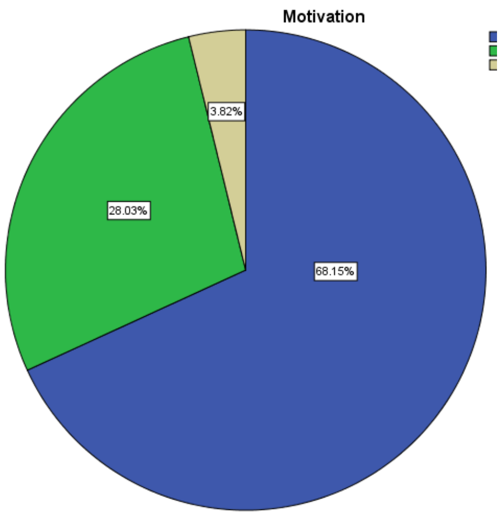


Figure 5.3: Patients' Motivation to Communicate Electronically

5.3 Descriptive Statistics

The survey questionnaire incorporated various constructs and their corresponding measuring items, each coded for ease of analysis. These constructs were Mobile Technology (MT), Environment (Envt), Culture (Cu), Attitude (Att) Beliefs, Skills, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioural Intention (BI), and Patients' Use of mHealth Self-Monitoring for Diabetes (mHealthSM). For instance, Mobile Technology (MT) had four measuring items denoted as MT1 through MT4, while Environment (Envt) had five attributes labelled Envt1 to Envt5. Similarly, the other constructs (Attitude, Beliefs, Skills, PE, EE, SI, FC, BI, and mHealthSM) were represented by specific coding and measuring items as outlined in the questionnaire. This standardized approach facilitated the systematic analysis and interpretation of the collected data across different dimensions of the study.

The descriptive statistics reveal respondents' perceptions across a spectrum of constructs, assessed using a Likert scale spanning from 1 (strongly disagree) to 5 (strongly agree). Notably, respondents generally hold favourable views towards Mobile Technology (MT), with a mean score of 4.2294 and a relatively low standard deviation of 0.61882 (see Table 5.2). Perceptions regarding the Environment (Envt) are moderately positive, with a mean score of 3.9582 and a standard deviation of 0.63288, indicating a balanced outlook among participants. Respondents exhibit moderately positive sentiments regarding Culture (Cu), giving a mean score of 3.9325 and a standard deviation of 0.65246.

Further analysis reveals a prevailing trend of positive attitudes across several domains. Attitudes (Att) are generally positive, with a mean score of 4.0301 and a standard deviation of 0.62419, while Beliefs are moderately positive, indicated by a mean score of 3.9979 and a standard deviation of 0.67772 (see Table 5.2). Additionally, perceptions of Skills are notably high among respondents, with a mean score of 4.0886 and a standard deviation of 0.63893, underscoring a confidence in individual capabilities.

Expectations also feature prominently in respondents' outlooks. Performance Expectancy (PE) is notably high, with a mean score of 4.0781 and a standard deviation of 0.72871, indicating a strong belief in the effectiveness of outcomes (see Table 5.2). Conversely, Effort Expectancy (EE) registers a more moderate outlook, with a mean score of 4.0000 and a standard deviation of 0.69576, suggesting a balanced expectation regarding the effort required.

Social Influence (SI) and Facilitating Conditions (FC) are perceived moderately, with mean scores of 3.9051 and 3.9958, respectively, suggesting a balanced influence and support system within the respondents' social and environmental contexts (see Table 5.2). Behavioural Intention (BI) exhibits relatively high levels, as evidenced by a mean score of 4.2025 and a standard deviation of 0.70569, highlighting a strong inclination towards intended behaviours.

Finally, respondents demonstrate positive perceptions regarding the use of mHealth technology for Diabetes Self-Monitoring (mHealthSM), with a mean score of 4.0949 and a standard deviation of 0.71194, indicating a favourable disposition towards leveraging technological solutions for health management (see Table 5.2). Overall, the data portrays a predominantly optimistic stance across various constructs, reflecting favourable attitudes, beliefs, and intentions towards mobile technology, environmental factors, cultural influences, and the adoption of mHealth solutions for diabetes management.

Table 5.2: Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
MT	158	1.00	5.00	4.2294	0.61882
Envt	158	1.00	5.00	3.9582	0.63288
Cu	158	1.00	5.00	3.9325	0.65246
Attitude	158	1.75	5.00	4.0301	0.62419
Beliefs	158	1.00	5.00	3.9979	0.67772
Skills	158	1.00	5.00	4.0886	0.63893
PE	158	1.33	5.00	4.0781	0.72871
EE	158	2.00	5.00	4.0000	0.69576
SI	158	1.00	5.00	3.9051	0.75722
FC	158	2.00	5.00	3.9958	0.76456
BI	158	2.33	5.00	4.2025	0.70569
mHealthSM	158	2.00	5.00	4.0949	0.71194

5.4 Evaluation of the Measuring Models for the Non-Moderated Constructs

From the path-weighting scheme, three measurements were evaluated, and these indicate relationships among constructs or latent variables (LV) that demonstrate regressions, the factor-weighting scheme that underlies factorial confirmatory analysis. This analysis demonstrates the correlation as well as the centroid weighting scheme that checks the signal ("+/- 1") of the relations among LV that demonstrate the sign of the correlations (Ringle et al., 2014). The measurement models of the non-moderated constructs are demonstrated in Figure 5.4 (see next page). Based on Figure 5.4, the measuring models are evaluated and after modifications and adjustments, the path models are then evaluated.

As demonstrated in the measurement model (see Figure 5.4), three values are obtained. These are the correlated values between the observed variables (OV) and the LV. The R^2 value of the model is also obtained, as well as the coefficient of the linear path regression between LVs. From the evaluation of the measurement models, the first aspect to be observed is the convergence validity obtained by observation of the average variance extracted (AVE). The AVE explains the portion of data for each of the constructs or LV. The variables are expected to averagely correlate positively with their respective constructs or LV. This should also be viewed as the average of the factorial loads squared (Ringle et al., 2014). Based on the Fornell and Larcker (1981) criteria, the values of the AVE should be greater than 0.50 (AVE > 0.50) for the model to converge with a satisfactory result. This implies that should there be variables with lower values of AVE < 0.50, the model should be adjusted by having items of variables with lower values eliminated.

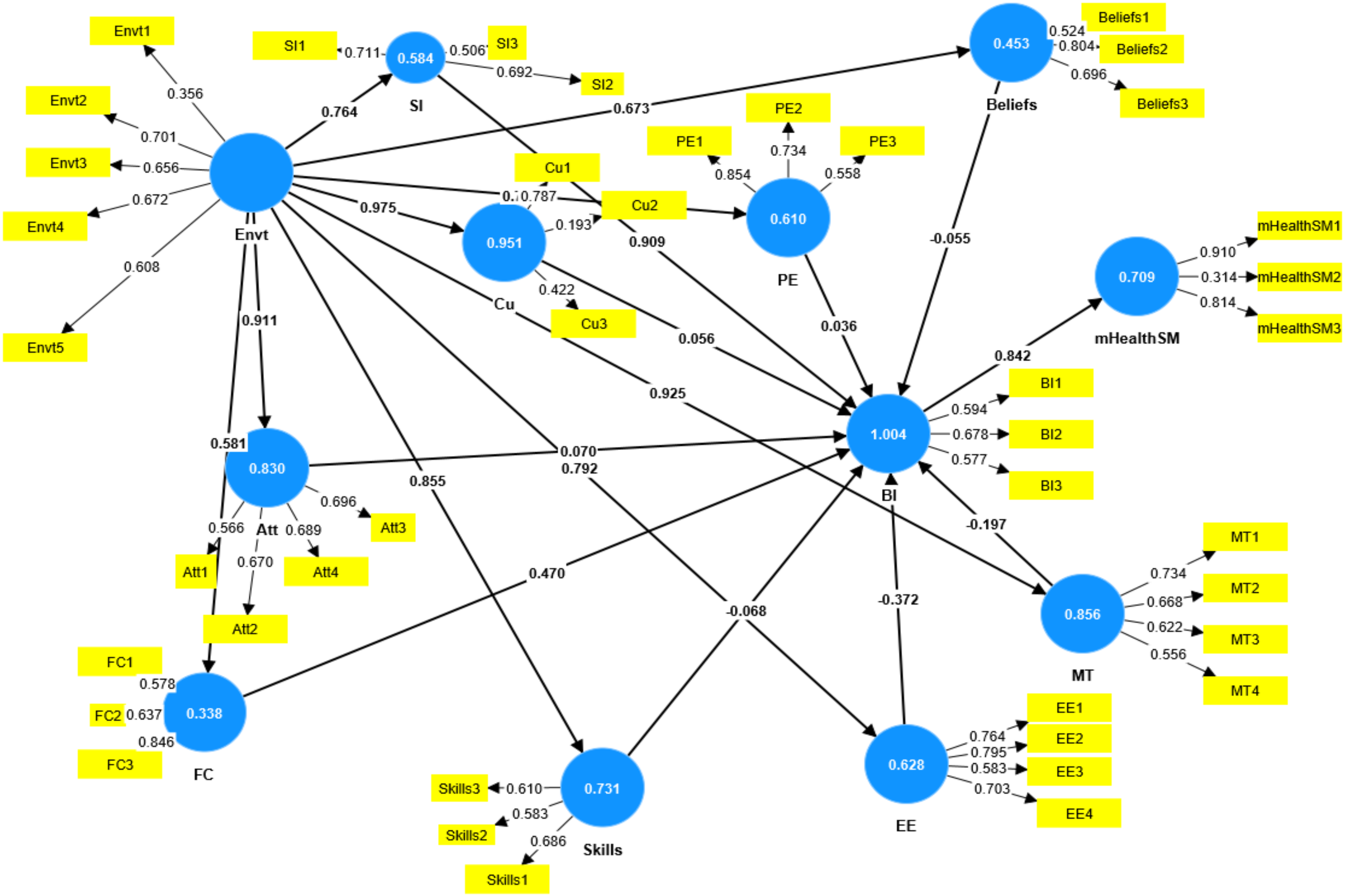


Figure 5.4: Measurement Models of Non-Moderated Constructs

The second aspect is to observe the internal consistency values (Cronbach's Alpha) and the Composite Reliability (CR) (Dillon-Goldstein's þ - rho). The CR is the most apposite for PLS, in that it prioritizes the variables according to their reliabilities. On the other hand, internal consistency measured by Cronbach's Alpha is highly sensitive to the number of variables in each construct (Hinton et al., 2014). The two measures, Cronbach's Alpha and CR, are used to explain whether the study's sample was free of bias. For suitability and satisfactoriness, their values should be above 0.60 and 0.70 for exploratory studies; and 0.70 to 0.90, respectively. Table 5.2 demonstrates the general view of the quality of the adjusted model by displaying the AVE, the constructs' reliability using Cronbach's Alpha, as well as the composite reliability of the measurement model.

Table 5.3: Construct Reliability and Validity

	Cronbach's Alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Variance Inflation Factor (VIF)
Attitudes	0.754	0.756	0.751	0.432	0.825
Behavioural intention	0.640	0.653	0.649	0.382	0.958
Beliefs	0.710	0.745	0.720	0.469	0.838
Culture	0.407	0.626	0.476	0.279	0.825
Effort Expectancy	0.806	0.816	0.806	0.512	0.935
FC	0.726	0.760	0.733	0.485	0.802
MT	0.738	0.749	0.741	0.420	0.813
Performance Expectancy	0.762	0.791	0.764	0.527	0.945
Skills	0.667	0.664	0.660	0.394	0.800
Social Influence	0.672	0.691	0.675	0.414	0.804
Environmental Factors	0.726	0.763	0.741	0.374	0.811
mHealthSM	0.752	0.847	0.747	0.530	0.926

As demonstrated in Table 5.3, Culture displayed values of AVE < 0.50, Cronbach's Alpha of 0.407 < 0.6, and composite reliability values of less than 0.7. These results suggest that cultural elements should be eliminated during the adjustment or modification of the model, or the construct should not be included in the final report. However, since in the conceptual model (see Figure 3.1) it was envisaged that Culture is moderated by Gender and Age, this construct was tested further to determine whether the moderating effects have any impact on its prediction.

The results demonstrated in Table 5.3 also indicate that most constructs had an AVE lower than the recommended threshold of 0.5 which suggests that the model needed modifications. The Variance Inflation Factor (VIF) values provided range from approximately 0.800 to 0.958, indicating very low levels of multicollinearity among the predictor variables in the regression model. With all VIF values comfortably below the typical threshold of 5 for concern about multicollinearity, there appears to be minimal to no issue with correlation among the predictors. This suggests that the predictor variables are not highly correlated with each other, which is advantageous for regression analysis. The low VIF values contribute to the stability and interpretability of the regression coefficients, enhancing the reliability of the model's predictions and insights. Overall, based on these VIF values, multicollinearity is not a significant concern in the regression analysis.

The third aspect was to evaluate the independence of constructs from one another by determining the discriminant validity (DV). Henseler, Ringle and Sarstedt (2015) suggest that with modern tools such as SmartPLS, the DV should be determined by using the heterotrait-monotrait ratio (HTMT) of the correlations. This function assesses the arithmetical or geometric mean correlation among indicators across constructs relative to the geometric-mean correlation among indicators within the same construct (Ringle et al., 2022). The absolute values of the correlations are then used to calculate the HTMT matrix for each construct. Henseler et al. (2015) state that good DV values should be in the range of, 0.7 < DV < 0.85. Should the value of HTMT be higher than the threshold, there is a lack of discriminant validity suggesting that the model should be adjusted. Other researchers, such as Fornell and Larcker (1981), indicate that values of DV not exceeding 0.9 may be accepted. However, if HTMT values are close to 1 it indicates a lack of discriminant validity. Table 5.4 illustrates the discriminant validity between constructs.

Table 5.4: Heterotrait-monotrait Ratio (HTMT) – List

	HTMT Ratio		**HTMT Ratio**
Behavioural Intention → Attitude	0.479	Skills → FC	0.755
Beliefs → Attitude	0.806	Skills → MT	0.772
Beliefs → Behavioural Intention	0.675	Skills → Performance Expectancy	0.949
Culture → Attitude	1.243	Social Influence → Attitude	0.699
Culture → Behavioural Intention	0.690	Social Influence → Behavioural Intention	0.909
Culture → Beliefs	1.019	Social Influence → Beliefs	0.793
Effort Expectancy → Attitude	0.882	Social Influence → Culture	0.980
Effort Expectancy → Behavioural Intention	0.581	Social Influence → Effort Expectancy	0.845
Effort Expectancy → Beliefs	0.664	Social Influence → FC	0.909
Effort Expectancy → Culture	0.924	Social Influence → MT	0.597
FC → Attitude	0.570	Social Influence → Performance Expectancy	0.864
FC → Behavioural Intention	0.964	Social Influence → Skills	0.911
FC → Beliefs	0.744	Environmental Factors → Attitude	0.941
FC → Culture	0.776	Environmental Factors → Behavioural Intention	0.545
FC → Effort Expectancy	0.537	Environmental Factors → Beliefs	0.681
MT → Attitude	0.766	Environmental Factors → Culture	1.165
MT → Behavioural Intention	0.351	Environmental Factors → Effort Expectancy	0.800
MT → Beliefs	0.674	Environmental Factors → FC	0.600
MT → Culture	0.949	Environmental Factors → MT	0.953

	HTMT Ratio
MT → Effort Expectancy	0.670
MT → FC	0.468
Performance Expectancy → Attitude	0.707
Performance Expectancy → Behavioural Intention	0.675
Performance Expectancy → Beliefs	0.608
Performance Expectancy → Culture	0.891
Performance Expectancy → Effort Expectancy	0.794
Performance Expectancy → FC	0.550
Performance Expectancy → MT	0.567
Skills → Attitude	0.933
Skills → Behavioural Intention	0.738

	HTMT Ratio
Environmental Factors → Performance Expectancy	0.785
Environmental Factors → Skills	0.865
Environmental Factors → Social Influence	0.760
MHealthSM → Attitude	0.613
MHealthSM → Behavioural Intention	0.824
MHealthSM → Beliefs	0.614
MHealthSM → Culture	0.783
MHealthSM → Effort Expectancy	0.622
MHealthSM → FC	0.680
Environmental Factors → MT	0.953
Environmental Factors → Performance Expectancy	0.785
MHealthSM → Skills	0.682
MHealthSM →Social Influence	0.784
MHealthSM → Environmental Factors	0.580

The discriminant validity of the constructs is also represented graphically as demonstrated by Figure 5.5.

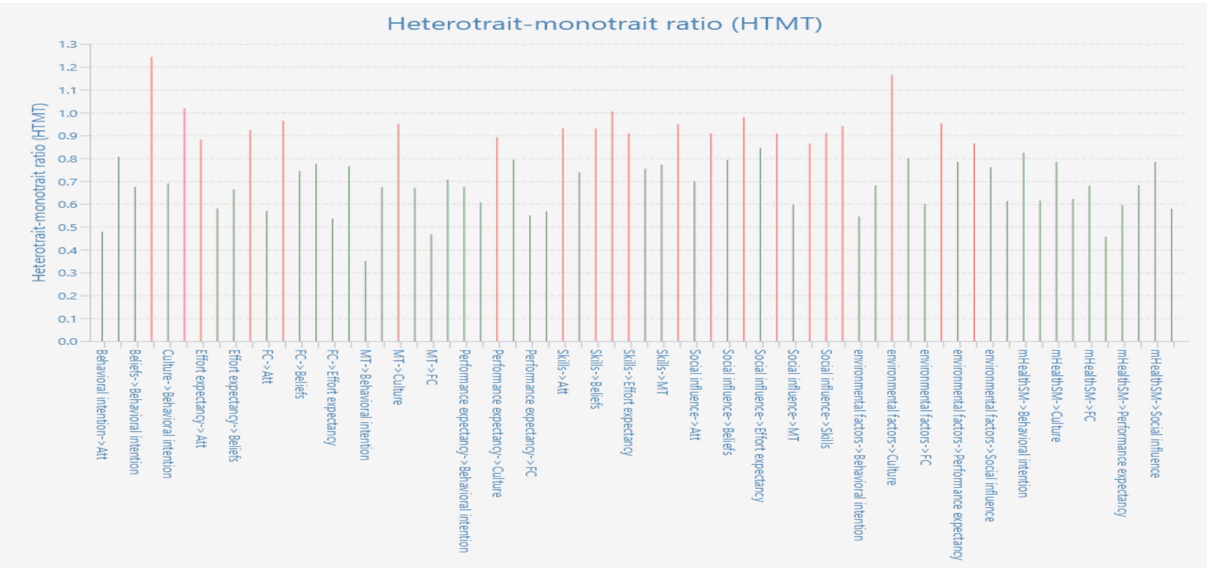


Figure 5.5: Heterotrait-monotrait Ratio (HTMT)

Table 5.5: Cross-loadings of Variables

	Att	BI	Beliefs	Culture	EE	FC	MT	PE	Skills	SI	Envt	mHealthSM
Att1	0,566	0,222	0,405	0,644	0,456	0,309	0,411	0,386	0,561	0,337	0,537	0,265
Att2	0,670	0,257	0,550	0,680	0,633	0,331	0,514	0,449	0,664	0,402	0,640	0,343
Att3	0,696	0,308	0,543	0,658	0,656	0,400	0,581	0,554	0,631	0,499	0,645	0,342
Att4	0,689	0,459	0,612	0,585	0,576	0,412	0,466	0,482	0,608	0,641	0,570	0,510
BI1	0,255	0,594	0,445	0,440	0,304	0,658	0,164	0,483	0,485	0,545	0,367	0,393
BI2	0,320	0,678	0,437	0,422	0,279	0,717	0,162	0,489	0,504	0,629	0,320	0,506
BI3	0,314	0,577	0,314	0,308	0,466	0,402	0,303	0,270	0,390	0,483	0,329	0,673
Beliefs1	0,447	0,421	0,524	0,536	0,324	0,472	0,389	0,386	0,546	0,483	0,286	0,403
Beliefs2	0,684	0,428	0,804	0,774	0,541	0,457	0,624	0,400	0,712	0,483	0,618	0,395
Beliefs3	0,507	0,496	0,696	0,528	0,478	0,570	0,328	0,450	0,675	0,590	0,431	0,400
Cu1	0,603	0,562	0,626	0,787	0,539	0,547	0,557	0,591	0,641	0,615	0,733	0,492
Cu2	0,360	-0,069	0,103	0,193	0,279	-0,159	0,200	0,168	0,141	0,054	0,295	0,015
Cu3	0,636	0,237	0,573	0,422	0,404	0,283	0,460	0,391	0,541	0,459	0,429	0,387
EE1	0,639	0,375	0,468	0,605	0,764	0,371	0,513	0,573	0,657	0,598	0,635	0,426
EE2	0,677	0,446	0,590	0,676	0,795	0,429	0,506	0,697	0,739	0,689	0,628	0,446
EE3	0,533	0,458	0,399	0,327	0,583	0,346	0,294	0,395	0,539	0,524	0,382	0,413
EE4	0,689	0,333	0,438	0,571	0,703	0,338	0,553	0,606	0,650	0,639	0,592	0,368
Envt1	0,415	0,062	0,296	0,385	0,284	0,036	0,361	0,237	0,286	0,225	0,356	0,186
Envt2	0,605	0,504	0,499	0,721	0,534	0,501	0,598	0,576	0,589	0,506	0,701	0,469
Envt3	0,554	0,344	0,479	0,579	0,500	0,426	0,687	0,459	0,624	0,474	0,656	0,315
Envt4	0,618	0,423	0,486	0,615	0,554	0,388	0,500	0,580	0,559	0,611	0,672	0,331
Envt5	0,583	0,221	0,267	0,639	0,503	0,299	0,653	0,464	0,493	0,449	0,608	0,311
FC1	0,400	0,524	0,446	0,399	0,417	0,578	0,335	0,423	0,498	0,612	0,386	0,473
FC2	0,394	0,583	0,398	0,389	0,306	0,637	0,344	0,214	0,435	0,478	0,418	0,476
FC3	0,385	0,867	0,633	0,504	0,378	0,846	0,282	0,505	0,648	0,694	0,421	0,468
MT1	0,437	0,154	0,377	0,509	0,379	0,337	0,734	0,266	0,407	0,442	0,707	0,266
MT2	0,470	0,269	0,534	0,571	0,364	0,303	0,668	0,306	0,502	0,318	0,603	0,294
MT3	0,534	0,242	0,444	0,590	0,553	0,265	0,622	0,452	0,577	0,348	0,565	0,270
MT4	0,539	0,209	0,373	0,412	0,441	0,246	0,556	0,483	0,503	0,430	0,507	0,216
PE1	0,607	0,620	0,525	0,633	0,656	0,500	0,535	0,854	0,861	0,722	0,636	0,485
PE2	0,540	0,426	0,442	0,607	0,639	0,395	0,439	0,734	0,667	0,629	0,624	0,388
PE3	0,387	0,403	0,301	0,479	0,432	0,288	0,201	0,558	0,510	0,538	0,417	0,369
SI1	0,552	0,643	0,447	0,619	0,751	0,496	0,376	0,684	0,712	0,711	0,540	0,608
SI2	0,528	0,587	0,497	0,603	0,512	0,509	0,457	0,594	0,586	0,692	0,563	0,522
SI3	0,275	0,495	0,527	0,325	0,350	0,705	0,294	0,366	0,472	0,506	0,345	0,334
Skills1	0,570	0,611	0,899	0,722	0,476	0,624	0,445	0,489	0,686	0,711	0,512	0,575
Skills2	0,618	0,395	0,392	0,402	0,621	0,409	0,456	0,619	0,583	0,552	0,528	0,321
Skills3	0,587	0,380	0,446	0,568	0,630	0,390	0,532	0,712	0,610	0,471	0,577	0,359
mHealthSM1	0,427	0,766	0,442	0,551	0,431	0,563	0,241	0,481	0,505	0,606	0,417	0,910
mHealthSM2	0,443	0,265	0,311	0,424	0,392	0,247	0,329	0,319	0,355	0,404	0,328	0,314
mHealthSM3	0,447	0,685	0,506	0,514	0,491	0,581	0,394	0,459	0,622	0,681	0,466	0,814

In Table 5.4 and Figure 5.5, the Culture and Skills constructs exhibit poor discriminant validity values, whereas most constructs have good DV values (below the threshold). These results confirmed the need for adjustment of the model, and also the exclusion of Culture from the final model. Another consideration was to the check for cross-loadings of the observed variables (OV) and the LV, as demonstrated in Table 5.5. When cross-loadings are applied, the component loading of an item on its parent construct should be higher than those of other constructs. Therefore, when an item loads better onto another construct than onto its parent construct, discriminant validity issues arise. When the difference between the loads is less than 0.10, cross-loading onto the other construct is indicated and discriminant validity is at risk (Henseler et al., 2015; Ringle et al., 2022). Table 5.5 illustrates the cross-loadings of variables.

The results in Table 5.5 indicate that most variables have higher cross loads to their parent construct than to other constructs. The exceptions were Culture, Skills and Environment constructs. This again demonstrated a need to modify the model.

5.5 Modification of the Measuring Models

Variance-based SEM using SmartPLS has no specific fit indices tested, such as with other measures. Hair, Hult, Ringle and Sarstedt (2017) approve the adoption of covariance-based SEM when SmartPLS fit indices are used. The Bentler-Bonett Normed Fit Index (NFI) is an incremental measure of goodness of fit that is widely applied because it is not affected by the number of variables in the model for fitness (threshold NFI > 0.90). Other measures are the root mean square residual (RMSR), whose threshold RMSR < 0.08, the squared Euclidean distance (d_ULS); and the geodesic distance (d_G) whose probability should be non-significant (p > 0.05). Lastly, there is the Chi-square (X 2) (Hair et al., 2017; Ringle et al., 2014, 2022). The model fitness is demonstrated in Table 5.6. The construct items were deleted from those variables that showed poor HTMT ratio of the correlations when carefully compared with the cross-loadings.

Table 5.6: Model Fit Summary

	Saturated model	Estimated model
SRMR	0.074	0.079
d_ULS	6.017	10.323
d_G	2.355	2.740
Chi-squared	1643.684	1860.735
NFI	0.906	0.954

After the model modifications, the path model was prepared for reading the R^2 and T-statistics for significance.

5.6 The Path Analysis Models

SmartPLS employs path analysis as a technique for assessing causal models by examining the relationship between a dependent variable and two or more independent variables (Hair et al., 2017). This helps to estimate causal connections in both magnitude and significance between variables. Consequently, a causal model is derived showing how independent variables influence dependent variables both directly and indirectly. From the path analysis, the nature of the model and the significance of the independent variables were obtained. The significance of the dependent variables explains their prediction power based on which the suggested hypotheses are tested.

5.6.1 Nature of the model

When using SmartPLS the values of R-Square (R^2), F-Square (F^2), and Q-Square (Q^2) are considered in explaining the nature of the model. According to Hair et al. (2017), R-Square statistics reflect the variance in the exogenous variable as shown in the endogenous variable(s); its values are 0.75 (substantial), 0.50 (moderate), or 0.25 (weak). On the other hand, the F square is the change in the R square when an exogenous variable is removed from the model and its values are interpreted as >=0.02 (small), >= 0.15 (medium), or >= 0.35 (large). Lastly, the Q-square measures the predictive relevance of a model by indicating whether it has predictive validity. Models with Q^2 values > 0 are considered predictively relevant. Table 5.7 illustrates the results obtained for the R-square in establishing the nature of the model.

Table 5.7: Quality Criteria Using R-Square

	R-squared	R-square adjusted
Attitude	0.830	0.829
Behavioural Intention	1.004	1.004
Beliefs	0.453	0.450
Culture	0.951	0.951
Effort Expectancy	0.628	0.625
FC	0.338	0.333
MT	0.856	0.855
Performance Expectancy	0.610	0.607
Skills	0.731	0.730
Social Influence	0.584	0.581
mHealthSM	0.709	0.707

As demonstrated in Table 5.6, two variables, namely, Beliefs, and facilitating conditions (FC) reflected R-Square values below 0.5. This implied that they are below moderate, although not weak since they were above 0.25.

5.6.2 Significance of independent variables of the model

Based on the procedure of bootstrapping, the analysis generated T-statistics for significance testing of both the inner and outer models of the structural path. The bootstrap result obtained approximates the normality of the data for a two-tailed test at different confidence levels. For a significance of 90%, the T-value should be 1.645 or greater at the 0.1 level. For 95% significance, the T-value value should be 1.96 or greater at 0.05 level. A 97.5% significance requires a T-value of 2.22 or greater at 0.025 level. Finally, the 99% significance level requires a T-value of 2.57 or greater at 0.01 level (Hair et al., 2017; Ringle et al., 2022). The significance of the independent variables is illustrated in Table 5.8.

Table 5.8: Mean, STDEV, T-values and P-values

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
Attitude → Behavioural Intention	0.703	0.419	0.076	9.280	0.013
Behavioural Intention → MHealthSM	0.842	0.850	0.074	11.377	0.000
Beliefs → Behavioural Intention	-0.554	-0.290	0.069	8.001	0.019
Culture → Behavioural Intention	0.056	1.318	40.526	0.001	0.999
Effort Expectancy → Behavioural Intention	-0.372	-0.561	0.072	5.203	0.028
FC→ Behavioural Intention	0.470	0.427	0.078	6.021	0.004

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
MT → Behavioural intention	-0.197	-0.302	0.096	2.043	0.037
Performance expectancy → Behavioural intention	0.636	0.891	0.209	3.043	0.021
Skills → Behavioural intention	-0.068	0.920	63.387	0.001	0.999
Social influence → Behavioural intention	0.909	-0.291	65.091	0.014	0.989
Environmental factors → Attitude	0.911	0.907	0.066	13.829	0.000
Environmental factors → Beliefs	0.673	0.682	0.095	7.078	0.000
Environmental factors → Culture	0.975	0.991	0.093	10.477	0.000
Environmental factors →Effort expectancy	0.792	0.791	0.064	12.427	0.000
Environmental factors → FC	0.581	0.589	0.139	4.169	0.000
Environmental factors → MT	0.925	0.923	0.071	13.049	0.000
Environmental factors → Performance expectancy	0.781	0.785	0.070	11.097	0.000
Environmental factors → Skills	0.855	0.877	0.112	7.639	0.000
Environmental factors →→ Social influence	0,764	0,777	0,075	10,203	0,000

As demonstrated in Table 5.8, three independent variables of culture, skills, and social influence contributed to the overall prediction that the model was not significant. As demonstrated in the conceptual model Figure 3.1, it was theorized that contributing factors are influenced by the patient's environment in using the mHealth self-monitoring system. This theorization was affirmed because the influence of environmental aspects was found significant for all independent variables.

5.6.3 Testing of the hypotheses

Based on T-statistics the suggested hypotheses were tested at 0.05 level (see Table 5.9).

Table 5.9: Hypotheses Testing

Hypothesis	T-statistic	P-value	Comment
H1a: Environmental aspects influence the performance expectancy of patients required to use mHealth for self-monitoring of diabetes.	11.097	p =.000 <.05	Accepted
H1b: Environmental aspects influence the effort expectancy of patients required to use mHealth for self-monitoring of diabetes.	12.427	p =.000 <.05	Accepted
H1c: Environmental aspects influence the social influence of patients required to use mHealth for self-monitoring of diabetes**.**	10.203	p =.000 <.05	Accepted
H1d: Environmental aspects influence the facilitating conditions of patients required to use mHealth for self-monitoring of diabetes.	4.169	p =.000 <.05	Accepted

Hypothesis	T-statistic	P-value	Comment
H1e: Environmental aspects influence the individual characteristics and attitudes of patients required to use mHealth for self-monitoring of diabetes**.**	13.829	p =.000 <.05	Accepted
H1f: Environmental aspects influence the individual characteristics and beliefs of patients required to use mHealth for self-monitoring of diabetes**.**	7.078	p =.000 <.05	Accepted
H1g: Environmental aspects influence the individual characteristics and skills of patients required to use mHealth for self-monitoring of diabetes**.**	7.639	p =.000 <.05	Accepted
H1h: Environmental aspects influence the culture of patients required to use mHealth for self-monitoring of diabetes**.**	10.477	p =.000 <.05	Accepted
H1i: Environmental aspects influence mobile technology use by patients adopting mHealth for self-monitoring of diabetes	13.049	p =.000 <.05	Accepted
H2: Performance expectancy influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	3.043	p =.021<.05	Accepted
H3: Effort expectancy influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes	5.203	p =.028<.05	Accepted
H4: Social influence influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	0.014	p =.989<.05	Rejected
H5: Facilitating conditions influence the patient's behavioural intention to use	6.021	p =.004<.05	Accepted
H6a: Individual's attitude influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	9.280	p =.013<.05	Accepted
H6b: The individual's beliefs influence the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	8.001	p =.019<.05	Accepted
H6c: The individual's skills influence the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	0.001	p =.999<.05	Rejected
H7: Culture influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	0.001	p =.999<.05	Rejected
H8: Mobile technology influences the patient's behavioural intention to use mHealth for self-monitoring of diabetes.	2.043	p =.037<.05	Accepted
H9: Behavioural intention has a directly positive influence on patients' use of mHealth for self-monitoring of diabetes.	11.377	p =.000<.05	Accepted

As shown in Table 5.9, all the suggested hypotheses were accepted other than for the variables of culture, individual characteristics and social influence which were rejected.

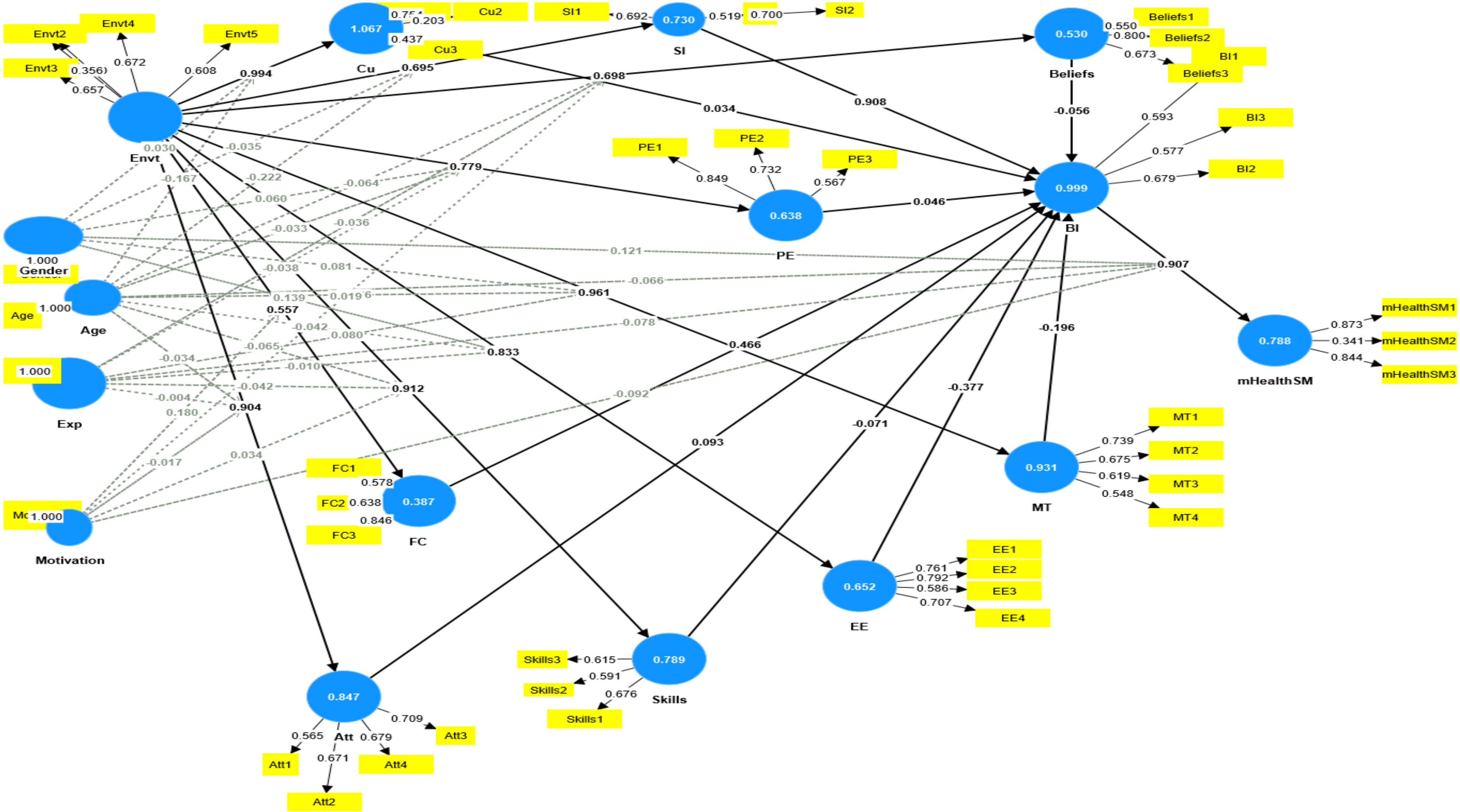


Figure 5.6: Path Models with Moderating Variables

5.7 Analysis of the Moderating Variables

This study suggested four moderating variables age, gender, experience and motivation. It was hypothesized that these variables moderate the independent variables' influence on patients' actions in using the mHealth self-monitoring system to adhere to medical prescriptions. To measure these interacting effects, the structural model was redesigned. The quality of the model was determined, adjustments made, and path analysis performed to read the new coefficients due to moderating effects, as demonstrated in Figure 5.6. The AVE, CR, and Discriminant Validity (DV) of the redesigned model were once again checked; and its fitness was adjusted to ensure that it met the satisfactory threshold values.

When a construct has a moderating effect on another construct, the third (moderator) variable impacts the relationship between two constructs. This implies that testing the moderating relationship involves analysing the interacting effects of the moderating variables applying to whether changes due to the moderator increase or decrease the intensity of the focal relationships (Becker, Ringle & Sarstedt, 2018).

Hence, SmartPLS uses a two-stage approach, which uses LV scores of the latent predictor. In this case, any of three options, namely, standardized, unstandardized or mean cantered, are used to compute the moderating effects.

The path models presented in Figure 5.6 demonstrate moderating effects on the relationships between latent and dependent variables. Figure 5.6 is the final adjusted model after achieving satisfactory threshold values for the validity of AVE, CR, and DV. Table 5.10 illustrates the results for significant interactions between the moderating and the independent variables, using the mean centre of both the moderator and the independent variable.

Table 5.10: Mean, STDEV, T-values, P-values of Moderating Variables

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
Age → BI	0.475	0.420	0.239	1.986	0.034
Age → Cu → BI	-0.131	-0.126	0.061	2.128	0.033
Age → MT → BI	-0.687	-0.823	0.503	1.367	0.172
Age → PE → BI	-0.316	0.018	0.714	0.443	0.658
Age → SI → BI	0.049	0.047	0.071	0.689	0.491
Age → mHealthSM	-1.527	-1.610	0.735	2.078	0.038
Age → Attitude → BI	-0.188	-0.087	0.038	4.925	0.003
BI → mHealthSM	0.638	0.650	0.068	9.315	0.000
Age → Beliefs → BI	0.249	0.053	0.072	3.458	0.027
Cu → BI	0.069	0.060	0.100	0.693	0.488
EE → BI	-0.538	-0.537	0.102	5.298	0.006
Envt → Attitude	0.692	0.692	0.062	11.122	0.000
Envt → Beliefs	0.508	0.515	0.065	7.840	0.000
Envt → Cu	0.657	0.659	0.065	10.062	0.000

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
Envt → EE	0.625	0.627	0.063	9.963	0.000
Envt → FC	0.432	0.443	0.093	4.652	0.000
Envt → MT	0.712	0.711	0.068	10.527	0.000
Envt → PE	0.591	0.602	0.077	7.707	0.000
Envt → SI	0.497	0.512	0.050	9.907	0.000
Envt → Skills	0.609	0.618	0.053	11.540	0.000
Exp → BI	-0.520	-0.463	0.074	7.054	0.002
Exp x FC → BI	-0.027	-0.028	0.072	0.372	0.710
Exp x MT → BI	0.629	0.773	0.503	1.249	0.212
Exp x PE → BI	0.293	-0.036	0.716	0.410	0.682
Exp → mHealthSM	0.353	0.436	0.075	4.689	0.001
Exp x FC → BI	0.501	0.485	0.095	5.277	0.000
Gender BI → mHealthSM	-0.106	-0.101	0.042	2.506	0.032
Gender x Cu → BI	0.079	0.078	0.059	1.324	0.185
Gender x MT → BI	0.060	0.057	0.065	0.911	0.363
Gender x PE → BI	0.124	0.119	0.080	1.559	0.119
Gender x SI → BI	0.219	0.211	0.082	2.660	0.008
Gender → mHealthSM	0.058	0.060	0.021	2.708	0.009
Gender x MT → BI	-0.424	-0.405	0.044	9.569	0.000
Motivation → mHealthSM	-0.469	-0.473	0.138	3.396	0.002
PE → BI	0.273	0.287	0.116	2.353	0.016
SI → BI	0.276	0.270	0.113	2.443	0.015
Age → Skills → BI	0.053	0.055	0.128	0.416	0.678
Exp x BI → mHealthSM	0.782	0.965	1.001	7.758	0.000
Age x BI → mHealthSM	-0.464	-0.608	0.072	6.483	0.000
Gender x BI → mHealthSM	-0.418	-0.415	0.098	4.286	0.000
Motivation x Attitude → BI	-0.622	-0.723	0.977	6.367	0.002
Motivation x Beliefs → BI	-0.682	-0.823	0.136	5.003	0.012
Motivation x Skills → BI	-0.587	-0.623	0.577	1.017	0.472
Motivation x BI → mHealthSM	0.350	0.395	0.082	4.739	0.000
Age x Envt → Cu	-0.312	-0.316	0.045	6.863	0.000
Age x Envt → MT	0.169	0.050	0.078	2.170	0.035
Age x Envt → PE	-0.281	-0.258	0.127	2.212	0.032
Age x Envt → SI	-0.164	-0.166	0.063	2.582	0.010

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T-statistics (|O/STDEV|)	P-values
Gender x Envt → Cu	-0.022	-0.032	0.056	0.397	0.692
Gender x Envt → MT	0.031	0.042	0.055	0.567	0.571
Gender x Envt → PE	0.012	-0.004	0.084	0.141	0.888
Gender x Envt → SI	-0.064	-0.069	0.067	0.964	0.335
Exp x Envt → FC	-0.162	-0.148	0.019	8.617	0.000
Exp x Envt → MT	-0.332	0.384	0.109	3.032	0.004
Exp x Envt → PE	0.224	0.078	0.054	4.165	0.000
Exp x Cu → BI	0.341	0.358	0.158	2.154	0.022
Exp x EE → BI	0.309	0.337	0.120	2.572	0.017
Age x EE → BI	-0.254	-0.284	0.129	1.969	0.041
Gender x EE → BI	0.480	0.476	0.138	3.473	0.001
Gender x Attitude → BI	0.374	0.362	0.073	5.112	0.022
Gender x Beliefs → BI	0.526	0.579	0.069	7.608	0.000
Gender x Skills → BI	0.783	0.811	0.530	1.477	0.081

Based on the results presented in Table 5.10, it was possible to determine the significance of the interacting effects of the moderating variables on the relationship between the independent and the dependent variables. When considering the T-statistic and the P-value for each relation, the suggested hypotheses were tested by comparing the significance of the interacting effects of the moderating factors. Where the significance was noted, it implied that the hypothesized interacting effects do exist; and where there was no significance shown, it implied no interacting effects exist. The tested hypotheses are illustrated in Table 5.11.

Table 5.11: Moderating Factors Hypotheses Testing

Moderating Factor	Hypothesis	T-statistic	P-value	Comment
Age	**H10**: The patient's age has a moderating effect on the influence of PE, EE, SI, IC, Cu and MT on behavioural intention such that the moderating effect is higher for younger patients than for older ones.			
	Age x PE→BI	0.443	p = 0.658 > .05	Rejected
	Age x EE → BI	1.969	p = 0.041 < .05	Accepted
	Age x SI → BI	0.689	p = 0.491 > .05	Rejected
	Age x Attitude → BI	4.925	p = 0.003 < .05	Accepted
	Age x Beliefs → BI	3.458	p = 0.027 < .05	Accepted
	Age x Skills → BI	0.416	p = 0.678 > .05	Rejected
	Age x Cu → BI	2.128	p = 0.033< .05	Accepted
	Age x MT → BI	1.367	p = 0.172 > .05	Rejected

Moderating Factor	Hypothesis	T-statistic	P-value	Comment
Gender	**H11**: The patient's gender has a moderating effect on the influence of PE, EE, SI, IC, Cu and MT on behavioural intention such that the moderating effect is higher in males than in females.			
	Gender x PE → BI	1.559	p = 0.119 > .05	Rejected
	Gender x EE → BI	3.473	p = 0.001 < .05	Accepted
	Gender x SI → BI	2.660	p = 0.008 < .05	Accepted
	Gender x Attitude → BI	5.112	p = 0.022 < .05	Accepted
	Gender x Beliefs → BI	7.608	p = 0.000 < .05	Accepted
	Gender x Skills → BI	1.477	p = 0.081 > .05	Rejected
	Gender x Cu → BI	1.324	p = 0.185 > .05	Rejected
	Gender x MT → BI	0.911	p = 0.363 > .05	Rejected
Experience	**H12**: The patient's experience has a moderating effect on the influence of PE, EE, FC, IC, Cu, and MT on BI and that of BI on mHealth self-monitoring usage, such that the moderating effects are higher in patients with experience than in those without.			
	Experience x PE → BI	0.410	p = 0.682 > .05	Rejected
	Experience x EE → BI	2.572	p = 0.017< .05	Accepted
	Experience x FC → BI	0.372	p = 0.710 > .05	Rejected
	Experience x Cu → BI	2.154	p = 0.022 < .05	Accepted
	Experience x MT → BI	1.249	p = 0.212 > .05	Rejected
	Experience x BI → mHealthSM	7.758	p = 0.000 < .05	Accepted
Motivation	**H13**: Motivation has a moderating effect on the influence of IC on BI and that of BI on mHealth self-monitoring usage, such that the moderating effects are higher when patients are highly motivated than in those with low motivation,			
	Motivation x Attitude → BI	6.367	0.002	Accepted
	Motivation x Skills → BI	1.017	0.472	Rejected
	Motivation x Beliefs → BI	5.003	0.012	Accepted
	Motivation x BI → mHealthSM	4.739	0.000	Accepted

The results presented in Table 5.11 indicate that some moderating variables have interacting effects on the influence of independent variables on dependent variables. For instance, Age has a moderating effect on effort expectancy (EE), individual characteristics of attitude (Att) and Beliefs, as well as on culture (Cu). The variable, Skills, as an attribute of individual characteristics, was found not to be moderated by any variables, and its influence on the dependent variable was not significant. Additionally, culture (Cu), which was not significant in the prediction of mHealth self-monitoring use, was positively moderated by Age and Experience to have a significant positive influence on the patient's behavioural intention to use the system.

5.8 Summary

This chapter presented the results that were obtained from an analysis of the collected data. Data were analysed using SmartPLS, a statistical tool that offers a graphical user interface for the modelling of variance-based structural equations applying the partial least squares path modelling method.

Using SmartPLS for analysis helped this study to assess both convergent and discriminant validity, as well as reliability, all core in structural equation modelling to give certainty that the obtained results as well as the designed model can be used with confidence. The chapter also discussed the interacting effects of moderating variables that helped to explain the links between the independent and dependent variables. Therefore, based on the findings of the study presented in this chapter, it is possible to explain why and under which conditions variables are related to one another. This is essential for simultaneously explaining contingent and indirect effects. The next chapter discusses the findings of the study and their implications for theory and practice.

CHAPTER 6: INTERPRETATION AND DISCUSSION OF FINDINGS

This chapter discusses and interprets the findings of the study in terms of theory and practice. The chapter first explains the findings of the study with reference to the set hypotheses and interprets them based on the theory and practice of mHealth self-monitoring. Furthermore, the chapter outlines the findings in terms of the objectives of the study by clearly indicating how each of the set objectives was achieved. Finally, the chapter discusses the findings and how those provided insights that led to a mHealth self-monitoring artifact development.

6.1 Discussion and Interpretation to the Hypotheses

Based on the conceptual model shown in Figure 3.1, this study formulated 18 hypotheses using the constructs of the model and four major hypotheses involving the moderating factors of age, gender, experience and motivation. The age, gender and experience moderating factors each gave rise to six sub-hypotheses whereas motivation had two hypothesized interacting effects. This section discusses the findings of these hypotheses and gives interpretations based on theory and practice.

a) **Environmental aspects:** As demonstrated in Table 5.9, all nine suggested hypotheses due to the environmental aspects (H1a to H1i) were accepted. It should be noted that there is a direct correlation between the ability to deliver health services and the number of health workers, their skill level, where and how they are deployed, and how they are managed. This makes the environmental aspects a critical factor. Generally, in developing countries, there is a bias of experienced and highly qualified medical personnel toward urban areas compared to rural settings (Kalema & Mosoma, 2019; Narsai et al., 2021). Such skewness normally disadvantages rural patients in terms of access to healthcare personnel, creating the need for a mHealth self-monitoring system.

   Urbanization has exacerbated the migration of healthcare personnel, creating poor access and equity in rural areas in the provision of healthcare; as well as inadequate monitoring of patients, especially those with chronic conditions (Matseke, 2023; WHO, 2019). The impact of environmental aspects was even more evident during the COVID-19 pandemic lockdown and resulted in an increase in mortality rates of patients with chronic conditions due to poor accessibility to medical facilities including human resources (Fekadu et al., 2021; Kendzerska et al., 2021). The findings of this study agree with the findings of many previous researchers, (such as Ekholuenetale et al. (2023), Mbogori and Mucherah (2019) and Chatterjee (2019)) who stress that environmental aspects are essential antecedents of health self-monitoring.

b) **Performance expectancy:** The hypothesis about this construct (H1a) was accepted. Performance expectancy, also known as expected benefits, is essential in that patients expect mHealth self-monitoring to be beneficial as a facilitator assisting them to take control of their lives. According to the respondents the mHealth self-monitoring system is likely to be perceived by patients as a tool for addressing the health inequities that have arisen from limited access and unmet needs, due to poverty levels and the failure of the government to provide sufficient health services to underserved communities.

   The significance of performance expectancy in encouraging behaviour to accept and use technology was emphasised by Taneja and Bharti (2022) in their review of various studies. These studies used UTAUT2 to predict actual usage. The study of Taneja and Bharti (2022) revealed that over 80% of similar studies found performance expectancy to be highly significant in soliciting actual technology usage. These researchers also noted that effort expectancy influences technology use. These findings agree with studies of previous researchers (such as Kalema and Mosoma (2019), Momani (2020), Narsai et al. (2021) and Venkatesh et al., 2012), who found that patients' perceptions of expected benefits from using technology is a key contributing factor to their actual use of technology. These authors posit that, as they expect benefits from technology use, patients develop trust in the mHealth self-monitoring system and this will contribute to the improvement of their health holistically.

c) **Effort expectancy**: The theorized relationship between effort expectancy and behavioural intention for patients to use the mHealth self-monitoring system (H1b) was found to be significant and the hypothesis was accepted. Effort expectancy, which in this study is considered to be the ease of use of the mHealth self-monitoring system, has been found significant in many studies, as the users' perceive that if the technology is easy to use they will be able to benefit from it (Taneja & Bharti, 2022). Another aspect of effort expectancy, as a result of the overall achievement of the mHealth self-monitoring usage goal, is that when patients find the system easy to use, they will increasingly trust the system. This will in turn build their self-efficacy, which is critical for proper usage.

In the case of this study, the expectancy of minimal effort may also be explained as the ability of the patients to own a mobile phone and the ability to read, interpret and understand with ease the text sent by the short message system (SMS) as a reminder of the need to comply with a medical prescription. The exponential growth of mobile phone ownership in developing countries means that the availability and accessibility of smartphones is no longer an insurmountable obstacle. Understanding and interpreting the SMS from the mHealth self-monitoring system is crucial to the daily routine adherence to prescribed medicine. The findings of this study agree with those of previous researchers (such as Islam et al. (2021 and Chifu et al. (2022)), who noted that patients' adherence to the daily routine medication prescription fosters a state of calm and comfort, minimising anxiety and stress. The resulting independence in monitoring one's own health is fundamental to improving one's quality of life. This ability could help chronic patients to live a long, meaningful and dignified life.

d) **Social Influence:** The influence of others on patients to engage in behavioural intention toward self-monitoring of mHealth was hypothesized (H1c), but the relationship was not found to be significant. This finding implies that the impact of social influence on patients' behavioural intention to use the mHealth self-monitoring system can be viewed from two different perspectives. First, when other people important to the patients try to influence their perception, social influence may not carry as much weight as when patients decide for themselves to use mHealth, after perceiving it as being beneficial in improving their lives by self-monitoring their health. However, when viewed from Wu, Zhang, Zhu and Liu's (2022) extended definition, social influence includes the support that the patients gain from the communities in their environment, such as information provision, social contacts and health groups, who may have a strong influence on their behavioural intention. This explains why, when moderated by gender (see Table 5.10), social influence does have a significant influence on behavioural intention to use the mHealth self-monitoring system.

Regarding chronic diseases and patient adherence to medical prescriptions, social influence presents a split understanding. Some patients may prefer to keep their sickness private; hence social influence may not be considered a contributing factor to the mHealth self-monitoring system (Wu, Zhang, Zhu & Liu, 2022). The findings of this study do not support those of previous researchers (such as Woldeyohannes & Ngwenyama, 2017; Kruse et al., 2019; Cruz-Ramos et al., 2022). These researchers argue that, in many instances people may not be familiar with new technologies such as mHealth. As a result, these people may be influenced more by others' attitudes and opinions which makes social influence an essential antecedent of mHealth usage.

e) **Facilitating conditions:** This study hypothesised (H1d) that the support received from health facilities, government and others, such as healthcare personnel, is essential for the positive change in behavioural intention of patients to use the mHealth self-monitoring system and this hypothesis was supported. Concerning healthcare systems, facilitation is in the form of four basic forms of help, namely financing, provision, stewardship and resource development. This includes human resources, physical infrastructure and support, as well as knowledge sharing (Wu et al., 2022). The implication is that the patient experience and satisfaction with the mHealth self-monitoring system depends on the availability of technical infrastructure such as the mobile network and bandwidth strength, support allowing health workers to reach rural communities, and support by health personnel when needed.

   The findings of this study agree with those of other researchers (such as Alam, Alam, Rahman & Taghizadeh, 2021; Kalema & Mosoma, 2019; Meier et al., 2020) who argued that successful implementation of the health system is highly dependent on the support of health institutions in designing, implementing, evaluating, and updating the instruments. These researchers indicated that such support should also come from the government which should put in place better healthcare and mHealth policies, strategies and standards.

f) **Individual characteristics:** In this study, individual characteristics were hypothesized based on three categories, namely, the patient's attitude toward the mHealth self-monitoring system, patients' beliefs about the use of mHealth, and patients' skills to use mHealth technology. Both the attitude and beliefs hypotheses (H6a and H6b) were accepted, whereas the skills hypothesis (H6c) was rejected. These findings imply that, when patients are aware that the use of mHealth for monitoring their health will improve their lives, they will develop a better attitude towards the system as well as a strong belief that their lives will improve. On the other hand, once a positive attitude and a strong belief have been developed, patients will not require extra skills to use the mHealth self-monitoring system. The findings of this study agree with those of Chatterjee (2019), Islam et al. (2021) and Wu et al. (2022), who assert that the use of mHealth empowers patients to manage healthcare efficiently and effectively, which allows them to develop positive attitudes, satisfaction and beliefs that they are on a better track to improving their lives.

g) **Culture:** The influence of culture on behavioural intention to use mHealth for patients' self-monitoring of their health was hypothesized (H7). However, this hypothesis was rejected. The findings imply that although culture is influential in some studies on technology acceptance and use, its influence on self-monitoring of health may not be noteworthy (Gerber et al., 2023; Kumar et al., 2023). Culture is in most cases considered an important factor in addressing inequalities and inequities in health, as well as essential in closing the gap on the social determinants of health. However, in the case of mHealth self-monitoring system usage for patients to monitor their health, the aspects of inequalities and inequities may not apply. A system has already been developed to assist patients regardless of their socio-economic backgrounds.

The findings of this study do not agree with those of previous researchers (such as Aldenaini et al., 2023; Chatterjee, 2019; Pourmand et al., 2020), who found culture to be a significant factor in using mHealth. On the other hand, this study's findings do agree with those of Asmah et al. (2022) who argued that patients with well-known chronic diseases will use mHealth without cultural bias and misconceptions about causes of the diseases; and will have no fear of the treatment provided.

h) **Mobile Technology:** This construct examined the influence of mobile technology on patients' behavioural intention to use the mHealth self-monitoring system. This hypothesis (H8) was accepted. Mobile health technology encompasses the use of mobile devices, such as mobile phones, iPads and others that can download healthcare apps and electronic healthcare records to treat and monitor patient health (Kruse, Betancourt, Madrid, Lindsey & Wall, 2022). The mHealth mobile technology architectures that have been developed almost all involve a smart mobile device, such as a phone, equipped with a special diabetes app and connected to a wearable device (Goldfine et al., 2020).

   The acceptance of this hypothesis signifies the importance of mobile technologies and their related attributes in the self-monitoring processes. Therefore, the findings agree with those of previous researchers such as Istepanian and Al-anzi (2018), Kalema and Musoma (2019) and Kruse et al. (2022), all of whom recognised that mobile technology is 'the pillar' of a mHealth self-monitoring system. The findings of this study confirm what Goldfine et al. (2020) maintain, that wearable technologies have the potential to boost the significance of the use of mHealth. These wearables have the potential to continuously monitor patients' medication use, more especially the routine of patients taking chronic medications.

i) **Behavioural intention:** The intention to behave was hypothesised to have a direct positive influence on the use of the mHealth self-monitoring system by patients in adhering to medical prescriptions (H9). This hypothesis was accepted. Behavioural intention has been found to be a significant mediating factor and a major antecedent of actual usage in many studies of adoption, acceptance and use of technology (Venkatesh et al., 2012; Momani, 2020; Taneja & Bharti, 2021). These findings imply that for people to decide whether to use a technology, they first have to make a behavioural change to perform that particular act. The findings of this study are in line with those of various researchers, such as Davis et al. (1989), Venkatesh et al. (2003, 2012), Momani (2020) and Cruz-Ramos et al. (2022). These researchers concur with Fishbein & Ajzen (1975; 1980) in emphasizing the importance of behavioural intention in enlisting approved behaviour.

6.2 Discussion and Interpretation in Relation with Moderating Factors

As demonstrated in the conceptual model in Figure 3.1, four moderating factors, namely age, gender, experience and motivation, were suggested to have interacting effects on the influence of the independent variables on the mediating variable behavioural intention, and the dependent variable use of the mHealth self-monitoring system. This section presents the discussion and interpretation of findings with the hypotheses that were set to test the existence of the interacting effects for each moderating factor, as demonstrated in Table 5.11.

a) **Age**: Hypothesis H10 posited that the patient's age has a moderating effect on the influence of PE, EE, SI, IC, Cu and MT on behavioural intention, such that the moderating effects are higher in younger than in older patients. The results indicated that moderating or interacting effects were observed with effort expectancy (EE), individual characteristics of attitude (Att) individual characteristics of beliefs (Beliefs) and culture (Cu). However, there were no interacting effects observed with performance expectancy (PE), social influence (SI), individual characteristics of skills (Skills) and mobile technology (MT). The findings imply that there are instances in which the interacting effects of age become salient. When using technology as in the case of this study, young patients adapt to the mHealth self-monitoring system more quickly than older patients. Hence effort expectancy, attitude and beliefs are strongly impacted by the age's interacting effects. This agrees with the findings of previous researchers such as Williams, Rana, Roderick and Clement (2016) and Tripathi and Shailja (2018). Similarly, young people may not have a lot of cultural beliefs relating to causes of chronic illness and hence they would be willing to take the opportunity of any form of treatment presented to them.

On the other hand, age did not have interacting effects on performance expectancy and social influence. The interpretation of these findings may be that once patients have a positive belief that the mHealth self-monitoring system is presenting benefits as an effective way to treat their chronic conditions, they will use the system regardless of their age. The mHealth system is similar to any mobile App and, because there is the pervasiveness of mobile telephony skills, insufficiency would not be a major hindrance to the use of mHealth self-monitoring systems. The findings of this study agree with those of previous researchers such as Jayeola et al. (2022), Woldeyohannes and Ngwenyama (2017) and Tripathi and Shailja (2018), all of whom deduce that once users perceive technology as useful to them, they will use it with no discrimination.

b) **Gender:** Patients' gender was hypothesized to have interacting effects on the influence of PE, EE, SI, IC, Cu and MT for behavioural intention such that the moderating effects are higher in males than in females (H11). Results indicated that gender interacting effects do exist with effort expectancy (EE), social influence (SI), individual characteristics of attitude (Att), as well as with individual characteristics of beliefs (Beliefs). On the other hand, the effects of gender interaction with performance expectancy (PE), individual skills characteristics (skills), culture (Cu), and mobile technology (MT) were found not to be significant, implying that there were no moderating effects.

These findings imply that in many instances younger males will be more enthusiastic about exploring technology than their female counterparts, thus familiarizing themselves with it and finding the mHealth system easier to use. Similarly, younger males are more influenced by their peers than female ones, and this stimulates their beliefs and attitudes towards technological innovation. The findings of this study are consistent with those of previous researchers such as Venkatesh et al. (2003, 2012), Becker et al. (2018) and Rahim et al. (2022), who emphasized the influence of gender on attitude and beliefs regarding use of technology.

c) **Experience:** Patients' experiences using mobile phones was hypothesized as having interacting effects on the influence of PE, EE, FC, Cu, MT on BI (H12) and that of BI on the mHealth self-monitoring usage, such that the moderating effects are higher in patients with experience than in those without. Results indicated that interacting effects of Experience do exist with EE, Cu and BI, but do not exist with PE, FC or MT. In this study the implication of these findings is that experience is essential for mHealth self-monitoring system usage. Patients with experience of using mobile apps will find the mHealth equally easy to use as compared to their counterparts with no experience. The findings of this study agree with those of previous researchers such as Jayeola et al.(2022); Tripathi and Shailja (2018); and Rahim et al. (2022), who posit that when users have experience with technology, they will develop self-efficacy; and this will help them to use any other systems or upgrades with ease. On the other hand, experience was found to have no interacting effects on FC and MT. This is because FC and MT are external to the patients, the former relating to the health institutions, while the latter has more to do with the system architecture.

d) Motivation: This study hypothesized that motivation has moderating effects on the influence of IC on BI and that of BI on mHealth self-monitoring usage such that the moderating effects are higher in patients who are highly motivated than in those with low motivation. The results indicated that there are moderating effects of motivation with BI on the use of mHealth self-monitoring systems usage and on the influence of individual characteristics of attitude (Att) as well as on individual characteristics of beliefs (Beliefs) towards BI. However, these do not exist in the influence of individual characteristics of skills on BI.

The implication of these findings is that motivation increases patients' trust and willingness and, as a result, they will develop positive attitudes and beliefs in using the mHealth system to monitor their health. The findings of this study are consistent with those of Venkatesh et al. (2012), Sheng and Simpson (2013) and Ashrafzadeh and Hamdy (2018) who hold that motivation is a major antecedent of behavioural change, and hence is essential to performing the behaviour. These findings also agree with those of Fogg (2020), who emphasized the role of motivation when using persuasive technology.

6.3 Discussion and Interpretation of Findings in Terms of the Research Objectives

Inequalities, inequities and unfairness hinder good health. For patients to receive good healthcare there is a need for equitable distribution of medical personnel care, health facilities and the support of healthcare provision and monitoring (El Turabi, Menon, Pérez & Tolub, 2022). In South Africa, for example, differences in geographical and spatial distribution reflect historical inequities, making chronic disease a major contributor to the high mortality rates (Rensburg, 2021). Health equity is of paramount importance, yet achieving it is a challenge for healthcare providers and government policy-makers. This calls for collective and individual efforts from healthcare providers, policy-makers and researchers to address this critical challenge. To respond to this call, this study set out to develop a contextualized model for a persuasive technological mHealth self-monitoring system for diabetic patients in South African communities. To achieve this goal, four objectives were set. This section discusses the findings according to the set objectives and goal of the study.

6.3.1 Discussion and interpretation of the first objective

The first objective of this study was to describe the South African health system and identify the challenges that prevent their health teams from closely monitoring patients with chronic diseases such as diabetes. In many developing countries, including South Africa, both communicable and non-communicable chronic diseases, have emerged across social groups and geographical locations (Rensburg, 2021). As a result, it is essential to ensure that proper and timely treatments are provided to patients across the board to ameliorate the effects of health conditions. In leveraging digital technologies, such as mHealth systems, a country's healthcare system can meet the needs of all the population, not just those who are adept at navigating it. Unfortunately, the people who need health and social care most are often the least able to access it due to heterogeneous challenges in developing countries (Kendzerska et al., 2021; El Turabi et al., 2022). Hence, healthcare systems should be focused on ensuring that everyone has access to healthcare regardless of their geographical location or spatial distribution.

To achieve the first objective, this study devoted Section 3.1, Sub-sections 3.1.1 and 3.1.2, to discussing the South African health system and identifying the challenges that could hinder it from closely monitoring patients with chronic diseases. The discussion highlighted that, in addition to the four major functions of a healthcare system (namely, financing, provision, stewardship and resource development) a good healthcare system should also be able to engage, analyse, expand and mitigate challenges (El Turabi et al., 2022). Regarding engagement, the healthcare system should discover with whom it should collaborate in bridging the identified healthcare gaps, and in making the populus aware as well as encouraging patients to receive needed healthcare and to adhere to the medical prescriptions (Kendzerska et al, 2021; Bacelar-Silva et al., 2022). However, healthcare personnel themselves need access to sufficient information and reliable data on chronic diseases to enable them to take care of the patients.

6.3.2 Discussion and interpretation of the second objective

The second objective of this study was to identify and analyse the technological, psychological, individual, social and external factors that influence patients' behaviours regarding interacting with technology in South Africa. The mHealth self-monitoring system which was introduced builds on existing persuasive technology to transfer healthcare services electronically to patients. Therefore, its design, development and implementation required consideration of several factors including system design (including user interface design), implementation of the mHealth app, social aspects of the acceptance and use of mHealth by individuals, institutional factors related to the mitigation of challenges and creation of opportunities for practical application, as well as the effectiveness of mHealth usage (Gerber et al., 2023; Goldfine et al., 2020; Fogg, 2020; Kruse et al., 2022).

To achieve this objective, this study devoted Sub-sections 3.2.1 and 3.2.2, as well as Section 3.3 to discussing these factors. This study used UTAUT2 as its foundation theory to examine the influence of factors (including environmental aspects, effort expectancy, performance expectancy, social influence, facilitating conditions, culture, individual characteristics and mobile technology) when mediated by behavioural intention. A systematic scientific approach of factor analysis and SEM was followed in analysing the collected data. To test the conceptual model suggested, factors including environmental aspects, performance expectancy, effort expectancy, facilitating conditions, individual characteristics due to attitude, individual characteristics due to beliefs, mobile technology and behavioural intention were found to contribute significantly to the use of the mHealth self-monitoring system by patients. These factors qualified to be used in the final model developed to achieve the goal of this study.

6.3.3 Discussion and interpretation of the third objective

The third objective of this study was to identify and discuss theories and models that could be used in the designing of the persuasive technology mHealth monitoring systems for diabetic patients in South Africa. As Fogg (2020) indicated, the designing of a persuasive technology model involves the integration of technological as well as individual behavioural aspects. On the other hand, the use of a mHealth self-monitoring system encompasses factors related to individuals' social aspects of acceptance and use of technology (Ajzen, 1988; 1991, Bandura, 1986; Davis et al., 1989; Fishbein & Ajzen, 1975; 1980 Venkatesh et al. 2003, 2012). In addition, following the recommendation of the Medical Research Council Evaluation Framework (2000) on the procedures to evaluate complex interventions in health, behavioural intervention theories were included. The theory of BCW and the TDF were also discussed (Reidy et al., 2020; Skivington et al., 2021).

Based on this understanding, the discussion of the theoretical aspects for the design of the persuasive technology mHealth self-monitoring combined aspects of these behaviour theories with other factors needed for the integration of technology with behavioural aspects (Momani, 2020; Taneja & Bharti, 2021; Reidy et al., 2020; Kruse et al., 2022). Therefore, to achieve this objective, this study devoted Sections 3.2 and 3.3 to discussing these theories, and later summarized their strengths and weaknesses in Table 3.1. This led to the design of the conceptual model shown in Figure 3.1.

6.3.4 Discussion and interpretation with the fourth objective

The fourth objective of this study was to use the Design Science methodological approach to incorporate persuasive technologies into mobile applications, and experts' knowledge to develop an mHealth model for empowering diabetic patients in South Africa to monitor their health. Researchers Nunamaker, Chen, and Purdin (1991) suggest that, when using the DSR methodology, research should integrate the system development into the research process. Such a model would combine theory building, systems development, experimentation and observations in a multi-methodological approach. Furthermore, Peffers et al. (2007) emphasize that in the development of the artifact, a search process that draws from existing theories and knowledge to proffer a solution to a defined problem must be followed.

To achieve this objective, this study followed the six steps of the DSR methodology recommended by Peffers et al. (2007). The first step of problem identification and motivation was set out in Chapter 1, Sections 1.3 and 1.6. Section 1.3 identified the research problem and Section 1.6 discussed the justification for the study. The second step of defining the objectives for a solution was covered in Sections 1.4 and 1.5, covering the research objectives and questions that this study attempted to achieve and answer respectively. This study has dedicated Chapter 7 to elucidating the third to the fifth steps, namely, artifact design and development, demonstration, and evaluation of the prototype using experts in the mHealth system. The last step of communication will be conducted in Chapter Seven of this thesis, as well as in the publication of this thesis and articles extracted from the study.

6.3.5 Discussion and interpretation related to the research goal

The goal of this study was to develop a contextualized model for a persuasive technology mHealth self-monitoring system for diabetic patients in South African communities. The design of the mHealth self-monitoring model incorporates the use of smartphone technology with an integrated wearable sensor app, as well as considering social aspects of the acceptance and use of technology by individuals. Figure 3.1 depicts the conceptual model that was designed to incorporate these various aspects. Based on the model, a measuring instrument was designed, and data that were collected were analysed statistically using SEM. The remaining identified factors for the resultant model are environmental aspects, performance expectancy, effort expectancy, facilitating conditions, individual characteristics due to attitude, individual characteristics due to beliefs, mobile technology and behavioural intention. The final model is illustrated in Figure 6.1 (see next page) based on which an artifact was developed, as explained in the next chapter.

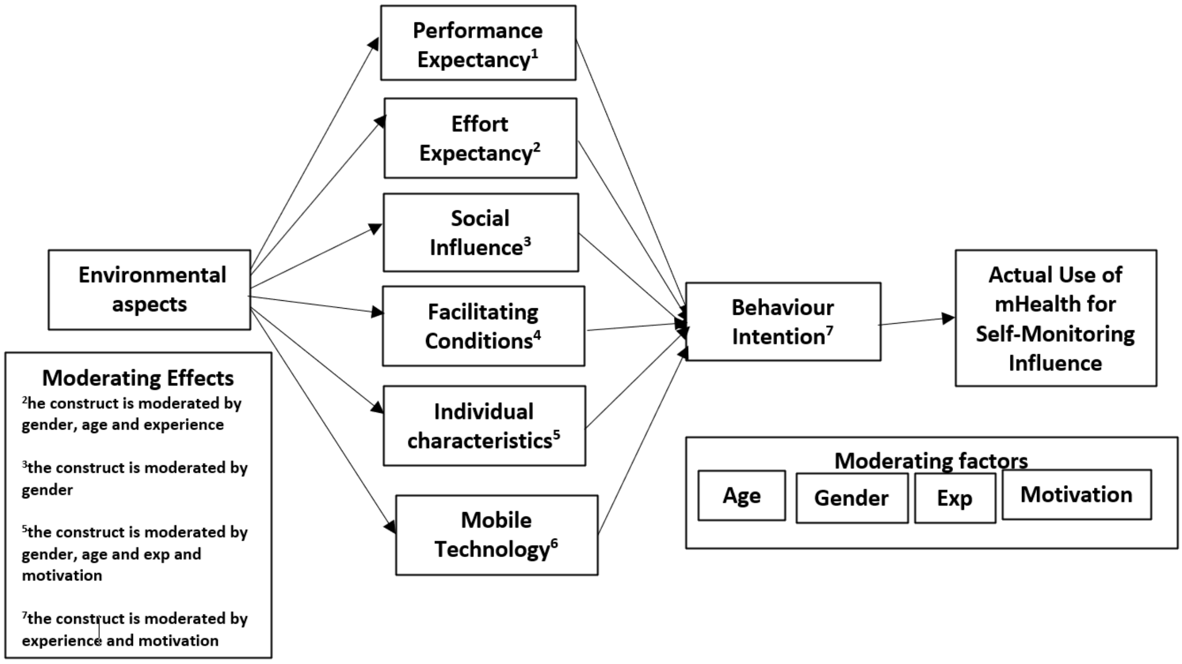


Figure 6.1: Model for mHealth Self-Monitoring

6.4 Summary

Patient self-monitoring of their health requires positive behaviours and lifestyle changes to comply with medical prescriptions. This study was based on theories of persuasive technology along with theories explaining behavioural aspects to design the model that could be used as a guideline for the implementation of a mHealth self-monitoring system. This chapter discussed the results obtained by testing the data collected, based on the conceptual model underpinned by UTAUT2. The discussion of results revealed that environmental aspects, performance expectancy, effort expectancy, facilitating conditions, individual characteristics of attitude and beliefs, and mobile technology factors are significant for the patients' behavioural intention to use a mHealth self-monitoring system. Other factors, namely social influence and culture, were only found to be significant after being moderated by gender and age, respectively. The model developed in this study acted as a cornerstone for the development of the artifact that is explained in the next chapter.

CHAPTER 7: ARTIFACT DEVELOPMENT

Chapter 6 discussed the findings of the study, including the set hypotheses and objectives. The chapter presented the final model based on the findings of the study. The developed mHealth self-monitoring model resulted in an abstract architectural design for the artifact of the mHealth self-monitoring system for diabetic patients. This chapter discusses the detailed procedures that were followed to develop the artifact. The chapter opens by specifying the requirements, both technical and non-technical, needed for the artifact to be developed. Thereafter, the chapter explains the architectural design and the development and evaluation of the artifact. In the evaluation of the artifact, this study leveraged the expertise of medical personnel and social workers to determine completeness, clarity, logical arrangement, correctness, reliability, usability and content validity.

7.1 The Design Overview

When following DSM, Peffers et al. (2007) emphasize the logical flow of six steps namely, problem identification and motivation, defining the objectives for a solution, artifact design and development, demonstration, evaluation and communication. Deng and Ji (2018) observed that several research studies have contributed to the general aim of developing a uniform DSR process model. Studies have concluded that the Peffers et al. (2007) model shown in Figure 7.1 is provides a full explanation. These authors indicate that in many Information Systems Research projects, design and development start with Step 3. These projects may be based on an existing artifact that requires customization, or may start from a conceptual artifact needing de novo development, as in the case of this study.

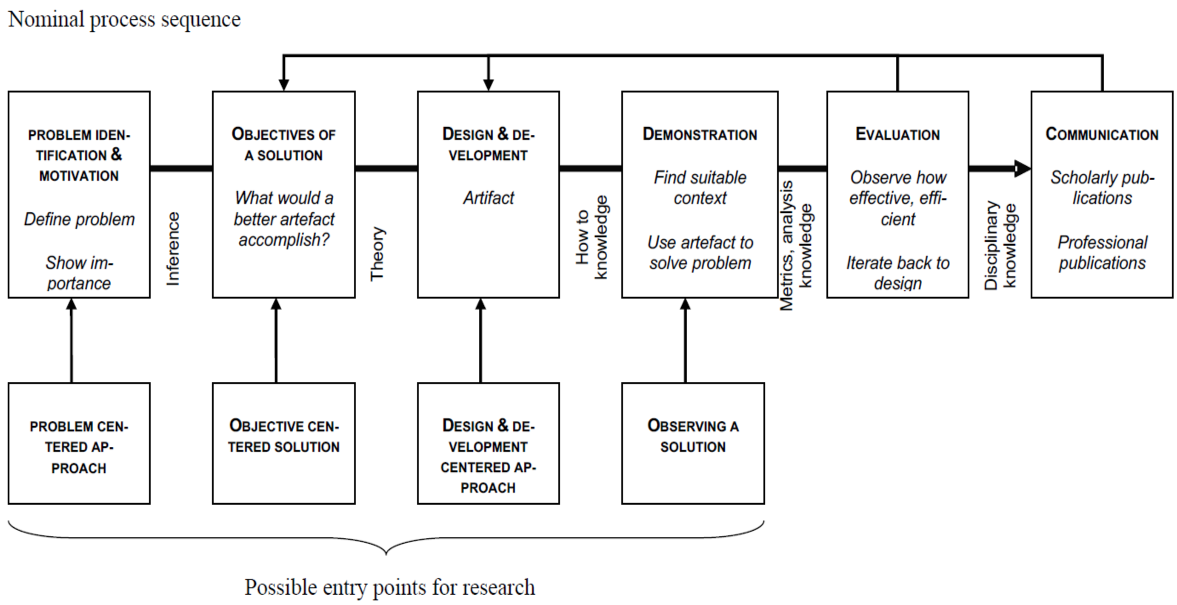


Figure 7.1: Design Science Research Process Model (*Source: Peffers et al., 2007*)

As depicted in Figure 7.1, the steps of problem identification and objective definition were covered in the previous chapters, hence this chapter concentrates on the remaining steps. This implies that, to conduct the design process, a conceptual understanding of the mHealth self-monitoring system had to be articulated first, together with systems requirements, including technical, functional, as well as non-functional requirements (Deng & Ji, 2018). This is followed by a detailed implementation process indicating the conceptual and physical design of the mHealth self-monitoring system.

7.1.1 The mHealth self-monitoring system architecture

A mHealth system is a mobile application that uses smartphone features such as phone contacts, push notifications, and social networking integration to remind patients, such as those who are diabetic, to take prescribed medication (Arsenijevic et al., 2020; Alam et al., 2021). In addition to social interaction, patients must be able to receive information about medical events, new drugs and the location of clinics when they interact with the mHealth system. The mHealth self-monitoring system is a solution designed to alleviate the lack of sufficient medical personnel and social health workers within medical institutions, particularly as a way to assist in patient monitoring especially for those patients who require routine medication. However, because of the rigid requirements (at set times and without fail) of routine taking of medicine, some patients with chronic complications find it a problem to adhere to a medical prescription. Hence there is a need to leverage persuasive technology (Jia, Yang, Zhou, Zhang, Lin, Chen, Cai, Yan & Ning, 2015). This study is based on Fogg's persuasive technology approach (2002, 2020) and integrates technology with behaviours to improve patient adherence, improve their execution ability, and improve compliance in daily healthcare.

Based on the Fogg Behaviour Model (Fogg, 2020) three basic aspects (namely, motivation, ability, and a prompt) have to be active simultaneously for a behaviour to occur. In persuasive technology, behavioural occurrence is seen as the goal achieved after aggregating other parameters (Fogg, 2002). This model is applied to the design of an artifact for an mHealth self-monitoring system as described in this study, by integrating a mobile app with patients' behaviour. The mHealth system is deployed on a smart mobile phone and is in a position to monitor the physiological status of a patient in an unconstrained manner, with simplified operations and following drug prescriptions detailed by medical personnel. The general architecture of the developed mHealth self-monitoring system is depicted in Figure 7.2 (next page). This architecture consists of devices that collect patient physiological information, implanted systems for signal processing, and wireless communication. More details of the system and its design requirements are discussed in the sections that follow.

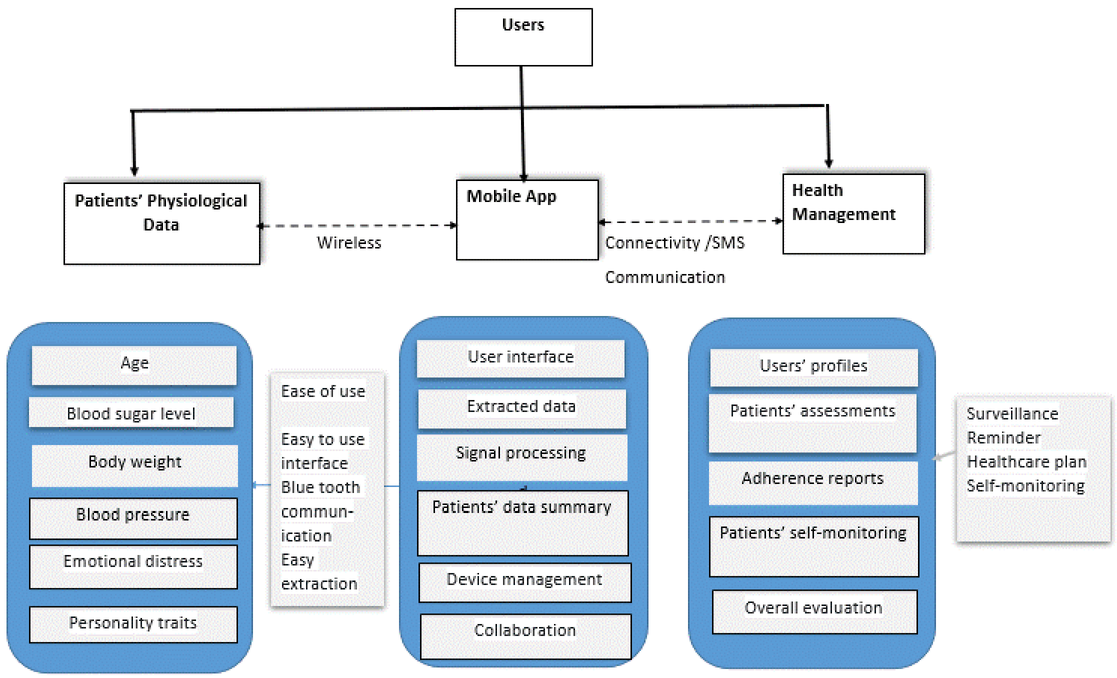


Figure 7.2: mHealth Self-Monitoring System Architecture (*Source: Modified from Jia et al., 2015*)

As shown in Figure 7.2, the architecture of the mHealth self-monitoring system consists of three major components, the collection of physiological data from patients, the design of the mobile application, and the health management system. The architecture demonstrates how the mobile application and the physiological data of the patient component communicate directly with each other, underpinned by the principles of ease-of-use. On the other hand, persuasive technology characteristics such as assessment, self-monitoring, patients' adherence and evaluation, are included in the health-management system.

7.1.2 The mHealth self-monitoring system functionalities

The self-monitoring mHealth system must have the ability to remind diabetic patients to take their medicines as prescribed by medical personnel, using features of the smartphone such as push notifications, search, contacts, and integration with social media networks (Moses et al., 2021). In addition to interacting socially, patients should have the ability to access other useful information regarding medical events, new drugs and clinics that offer services. Therefore, before designing the self-monitoring mHealth system, it is essential to establish all relevant functional requirements of the system.

In computing research that involves the design of software or a system project, performing a requirement analysis is a crucial steps in achieving its success. These requirements are generally categorized into functional or non-functional requirements. Ushakova et al. (2021) define non-functional requirements as a means of increasing the functionality of the system by identifying the system's operational capabilities and limitations. On the one hand, functional requirements refer to the components of the system used to perform the required tasks, that is inputs, outputs and processes. For a system design, basic non-functional criteria are expected to be addressed during software architectural design. The descriptions of the features and dependencies of the mHealth self-monitoring system are illustrated in Table 7.1.

Table 7.1 demonstrates what the mHealth self-monitoring system must do, including its features, functions, descriptions, and dependencies.

Table 7.1: Features and Dependencies of MHealth Self-monitoring System

Feature	Function	Description	Dependencies
Registration	New patients (sign up with username and password). New patients may also sign up using their existing social media accounts, such as Facebook, Twitter and Google accounts.	This function manages the user set-up process on the mHealth system using username and password.	First name should be provided. Last name should be provided. Date of birth should be provided. Physical address should be provided. Preferred app language must be selected (i.e., English, isiZulu, Khosa, Tshwana). Terms and conditions must be agreed to. Patient must not have previously been registered.
Patient verification	Log in	This manages the login process for patients on the mHealth system.	Correct patient's login details must be provided. Patient's details are validated and logged in to mHealth.
	Log in after the session timeout.	This manages patient's login to the app after the session timeout.	Correct login details must be provided. Patient's details are validated and logged in to mHealth.
	Log out	This manages the log-out of patients from mHealth system.	The patient must already be logged in.
Push notification	Instant Alert	This allows patients to view notifications reminding them to take their medicine.	Receiving notifications does not require the patient to be logged in. Patients should be in a position to toggle push notifications to "ON".
Connection to social media account	Connect to Facebook, Twitter, Instagram, etc.	This system function manages user authorization to connect to the patient's social account using account details.	Correct login details are provided. Connection to social account as authorised by the patient.
Utility	Calendar, events, weather, etc.	This enables patients to set up and view their scheduled events, appointments, weather, etc.	Patients must already be logged in.
News feed	Diabetes news and new developments, government announcements, and health programmes. Pharmacy-related information	This enables patients to view health news and trends from health portals and government sites. Patients should be able to get the latest information about the nearest pharmacies and health centres.	Patients must already be logged in.
Products and services	Available health products and clinic locator	This enables patients to locate the nearest hospital or clinic, pharmacies, etc.	Patients must already be logged in.

Feature	Function	Description	Dependencies
Contact	Add, view, modify and delete contacts.	This enables patients to add new contacts of health personnel and health workers.	Patients must already be logged in. Contact type (i.e., doctor, nurse, social worker, pharmacy, clinic, hospital) must be selected. All compulsory details should be provided.
Messages	View and create messages and reminders.	This allows patients to view email and SMS messages from contacts and the system-generated messages. Patients receive medication reminder messages indicating the time and date of refill. This functionality also helps patients set medical appointments.	All compulsory details should be provided, such as login and other related credentials, including the patient's surname and identification number.
Dashboard	Personal activities dashboard, Health portal dashboard, Patient's profile	This allows patients to view charts on the actual activities.	Patients must select the month or year view tab to display the dashboard. Patients must already be logged in.
Report	Monthly report on medicine collections, refills, visits	This function allows patients to view summarized reports on various activities. The reports should be exportable to PDF and Excel format.	Patients must select the date range to view the report. All compulsory details should be provided.
Home screen	Newsfeed, social feed, weather, products and services	This function allows patients to view a short menu.	Patients must already be logged in.

On the other hand, the specific MHealth self-monitoring system functionalities that describe how well it should operate are detailed as follows.

i. **Productivity**: The mHealth self-monitoring system based on a Mobile App should mimic the socially structured way in which patients interact with medical personnel or social workers during the consultation process. The system should remind patients to take medicine when it is time to do so as prescribed by the medical personnel.
ii. **Access to information**: The mHealth self-monitoring system should enable patients to access the latest information about diabetes, new drugs on the market, and some best practices.
iii. **Training**: The mHealth self-monitoring system should enable patients to easily access training materials about self-care for diabetics.
iv. **Access to diabetes national programmes**: The mHealth self-monitoring system should enable patients to access information regarding diabetes national programmes, events and possible funding. The system should integrate into existing government health portals to deliver information to patients.
v. **Security:** The mHealth self-monitoring system should ensure authorization to limit systems and data access and hence to enhance security controls. This also implies that the system should be interoperable, connecting seamlessly with existing security infrastructure and

processes for user authentication and authorization related to the health institution where the patient is registered.

vi. **Trust:** The mHealth self-monitoring system, through security enhancements, should increase trust by patients. This implies that the design of the system should comply with data governance principles, policies and controls while following strict data quality rules.

vii. **Scalability**: It has been observed that patients with Type 1 diabetes cannot regulate their blood sugar levels properly. This requires them to take insulin throughout the day (Gerber et al., 2023; WHO, 2020). Random clinical trials are conducted frequently to test the efficacy of new medications and treatments. These may lead to new interventions, additional information and knowledge. Therefore, the mHealth self-monitoring system is likely to need to be updated from time to time to accommodate these new developments, making scalability an essential feature of the system to be considered design.

7.1.3 mHealth Integration with persuasive technology for self-monitoring

The Fogg Behaviour Model (FBM) was leveraged to integrate persuasive technologies in mHealth for self-monitoring. According to Fogg (2009), the behaviour model of persuasive technology should embrace three aspects namely, sufficient motivation, ability and effective triggers. This implies that for an individual's execution ability to improve, reaction to a stimulus brought about by adequate and appropriate triggers as well as persuasive messages must work hand-in-hand. Such cooperation will elicit positive motivation to improve the ability to initiate self-monitoring behaviour. The design process for the introduction of self-monitoring behaviour is demonstrated in Figure 7.3. During the design process, the five persuasive strategies derived from Fogg's (2009) FBM, namely, investigation, assessment, patient health plan, self-monitoring and evaluation should receive attention. These were incorporated into the system to enhance the execution ability and adherence of patients.

In the case of this study, the Fogg (2009) five persuasive strategies linked to five stages depicted in Figure 7.3 were set to perform the following tasks:

i. **Investigation**: This stage involved extracting information about individual patients, including motivation, patient capacity and attitude toward healthcare. The individual characteristics, features and demographics, including age, body mass index, as well as the history of diseases are integrated at the point of investigation.

ii. **Assessment**: This stage quantitatively analysed the patient's health profile, including motivation level, ability to execute tasks, patient's health status and lifestyle.

iii. **Patient's healthcare plan:** Chronic disease patients such as those with diabetes are encouraged to have their healthcare plan that can include, among other items, exercise and diet that should be observed and conducted routinely.

iv. **Self-monitoring:** This stage is concerned with regular healthcare including the patient's healthcare management. The design of this process was based on the overall monitoring strategy, including electrocardiography to monitor heart functionality. Based on this stage, the reminder and control strategies are implemented (Jia et al., 2015; Arsenijevic et al., 2020).

v. **Evaluation:** As demonstrated in Figure 7.2, at the architecture level of healthcare management, medical personnel must check patient performance and adherence to instructions; and this should be evaluated to verify whether the patient responds positively to the self-monitoring system of mHealth. It is at this stage that a decision is made as to whether the patient should continue with self-monitoring or should be placed under administration by healthcare workers.

The design process of the mHealth self-monitoring system follows an iterative system that incorporates patient feedback and evaluation by medical personnel of how patients have behaved toward the system triggers, as demonstrated in Figure 7.3.

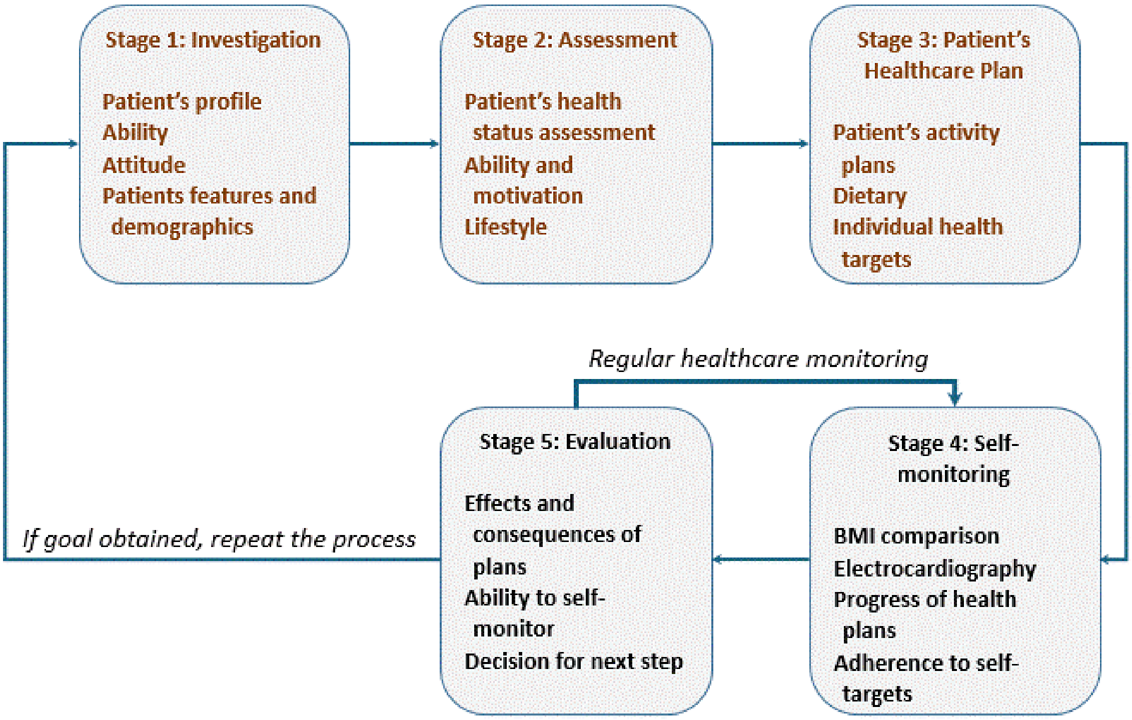


Figure 7.3: mHealth Integration with Persuasive Technology For Self-Monitoring (*Source: Modified from Fogg, 2009; Jia et al., 2015*)

7.2 Physical Design and Coding of MHealth Self-monitoring System

The development of the artifact covered the fundamental needs of individual health self-monitoring. The mHealth self-monitoring system for this study is an Android application designed with Kotlin programming using the Android Studio working integrated development environment (IDE). The Kotlin programming language is a recent language that ensures code safety and developer satisfaction for professional Android developers. The following tools were used to provide a fully-fledged self-monitoring system for mHealth.

- Firebase Real-Time Database: This is a cloud (online) NoSQL database that stores and synchronises data between users in real-time. In this study, the Firebase Real Time Database was used to store information about the registered patients on the mHealth system.
- Android Studio: This is an integrated development environment (IDE) designed specifically for Android development. In this studio, the Android Studio Chipmunk was utilized. The Chipmunk allows the inspection and debugging of the animation features built in a composable preview.
- Android Mobile Phone: The developed system was deployed on the Android mobile phone to run the application.

7.2.1 Coding and graphical interfaces

The system's front end and back end were developed and deployed on the Android phone; the codes for the two ends are as illustrated in Figures 7.4, Figures 7.5 and 7.6. Figure 7.4 demonstrates the coding, whereas Figure 7.5 gives the output on the graphical interface.

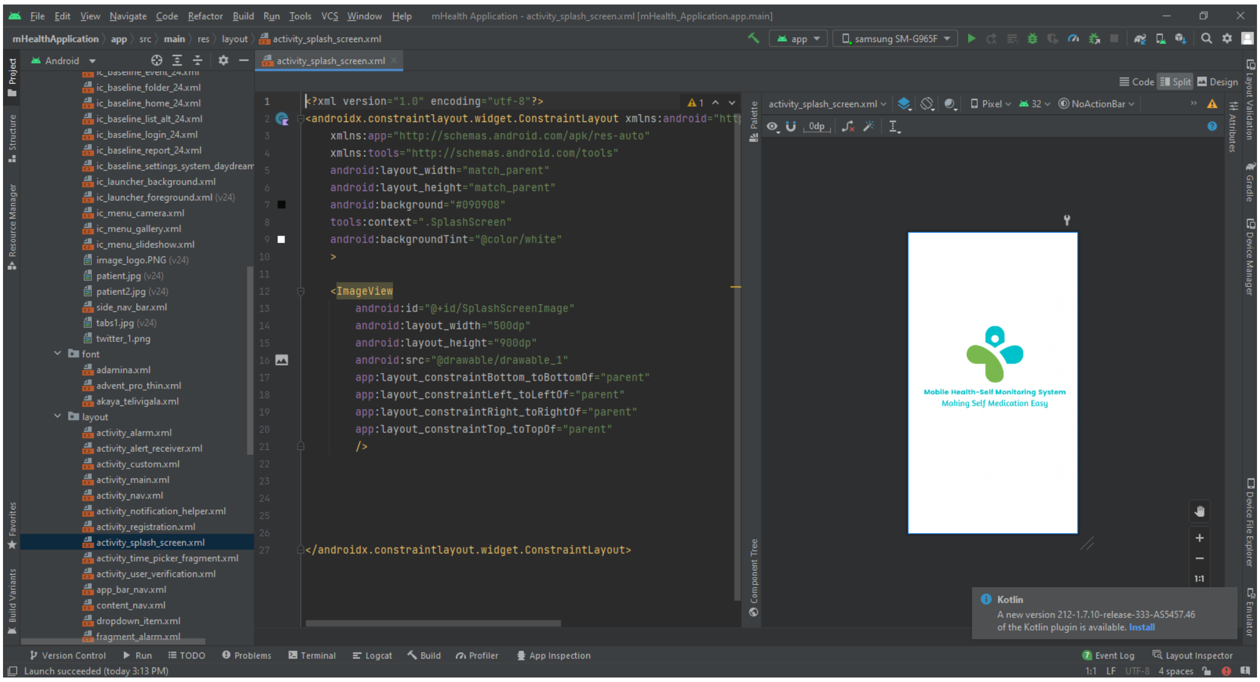


Figure 7.4: mHealth Self-Monitoring Front End

The graphical output of the front end is illustrated in Figure 7.5.

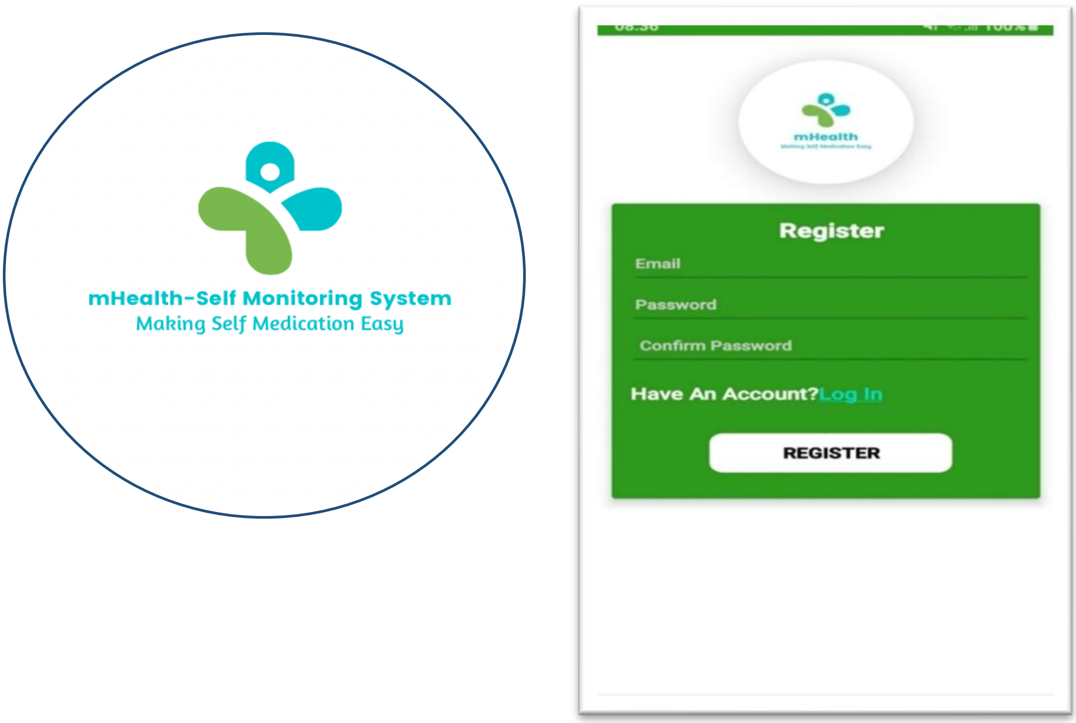


Figure 7.5: Graphical Output of the Front End

As demonstrated in Figure 7.4, the development of the front end incorporated the home screen or the landing page where the patient starts to perform the first activity on the system, registering or logging, to begin accessing the system. Each functionality as demonstrated in Table 7.1 has both a front end and a back end, with the front end being the patient's interface which facilitates interaction with the system, while the back end displays what happens in the system when a function or command is issued. The back end of the landing page is illustrated in Figure 7.6.

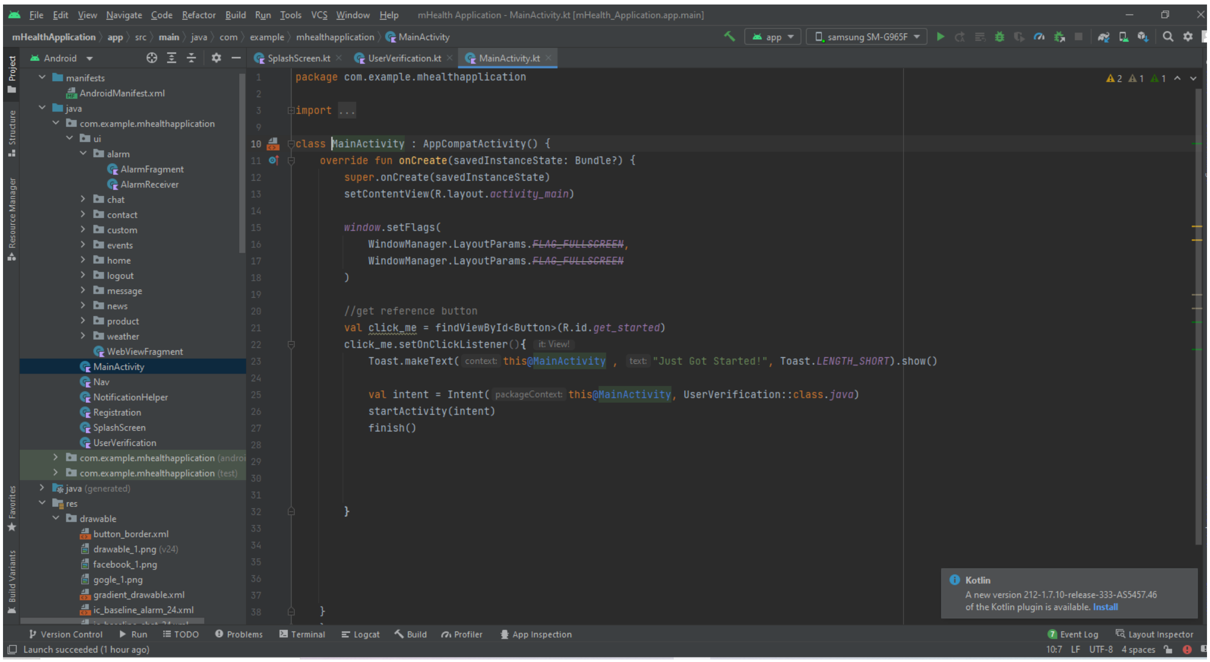
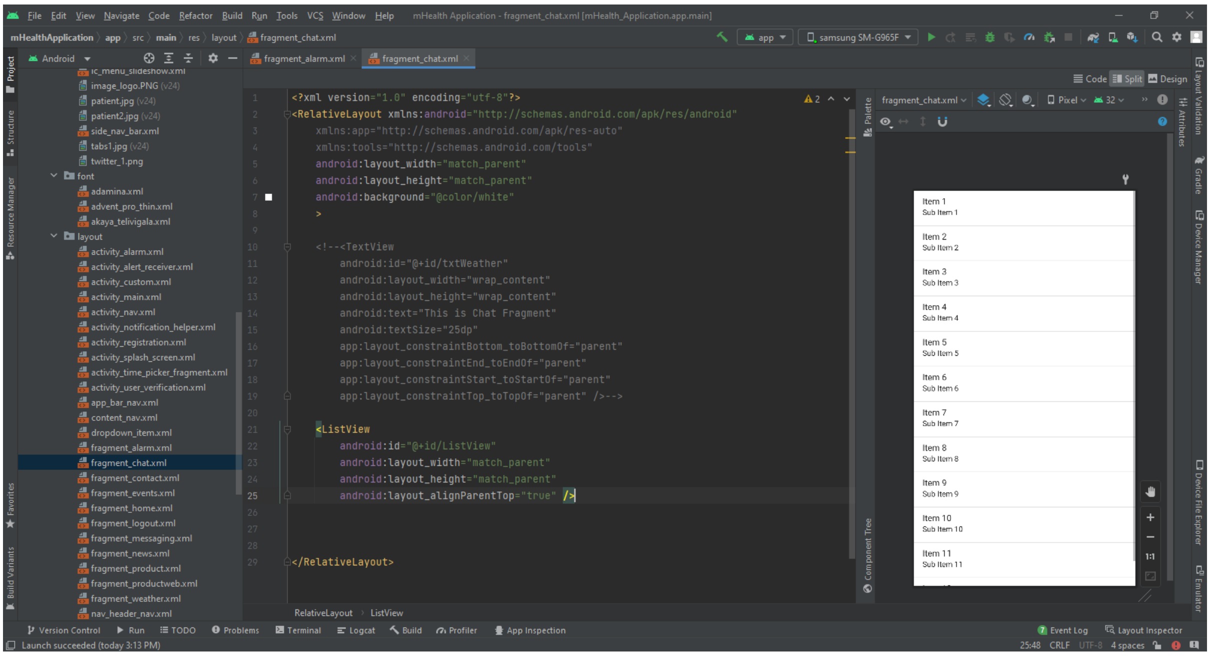


Figure 7.6: mHealth Self-Monitoring Back End

The landing page contained welcoming remarks for the patient and a button that the patient must click on to move to the next page. As explained in Table 7.1, a patient must either register or login to access the other functionalities that are found on the home page. The purpose of the login page is mainly to verify that the patient is already registered on the system. Accepted login credentials are short user names or email addresses and a password that a patient must use consistently in all interactions with the system. Successful login leads to navigation of the system which occurs after landing on the home page.

The objective of the mHealth self-monitoring system is to remind the patient to adhere to the medical prescription at the time recommended by the medical professional or social worker. The system is designed in such a way that it makes two contacts to remind the patient to take medicine. It first sends a preliminary message to alert the patient. At the exact time set for medicine-taking, an alarm automatically sounds - this is the second approach. Figures 7.7 and 7.8 illustrate the messages and the reminder front end and back end coding, whereas Figure 7.9 presents the graphical output. The patient can also schedule and create personal alarm notifications on the App. The patient clicks on the icon on the bottom left corner of the window; and then sets the exact time the alarm should sound by sending a ring notification at the appropriate time.



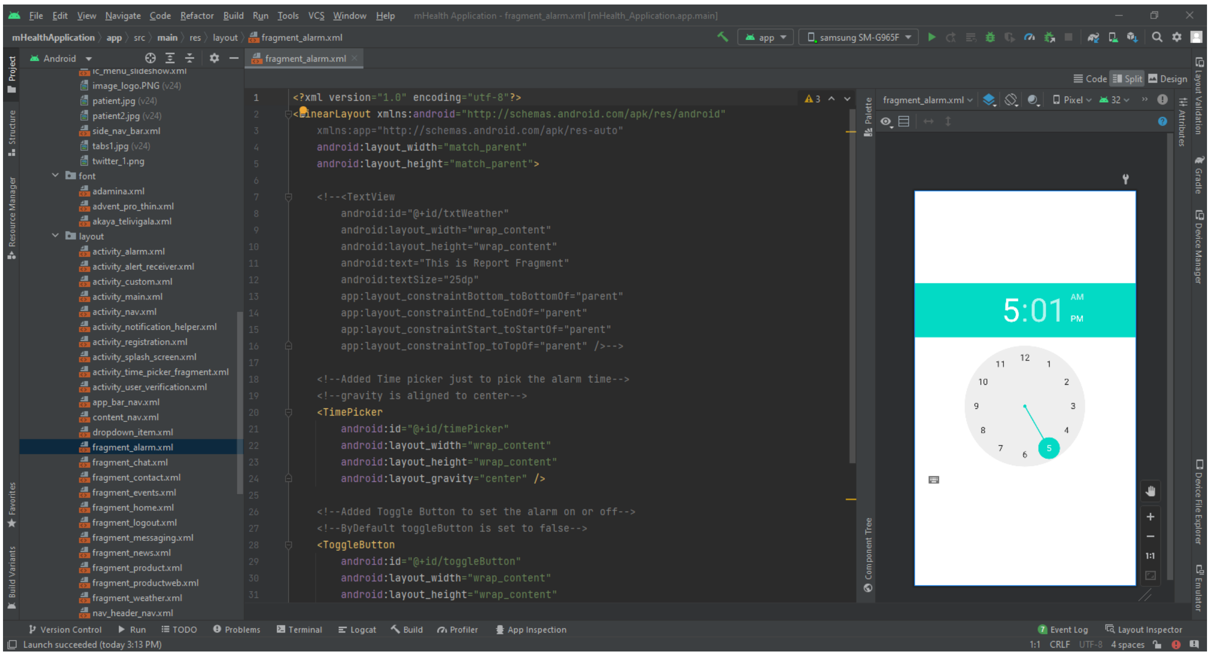
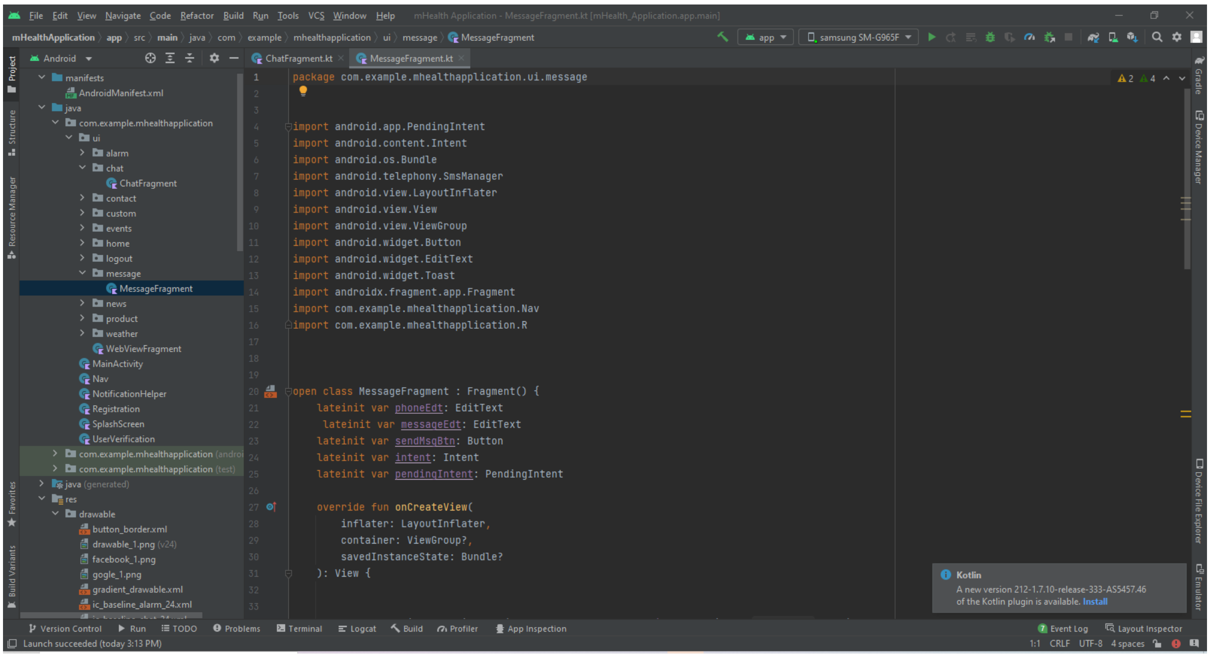


Figure 7.7: Notification and Reminder Front End

The back end is demonstrated in Figure 7.8.



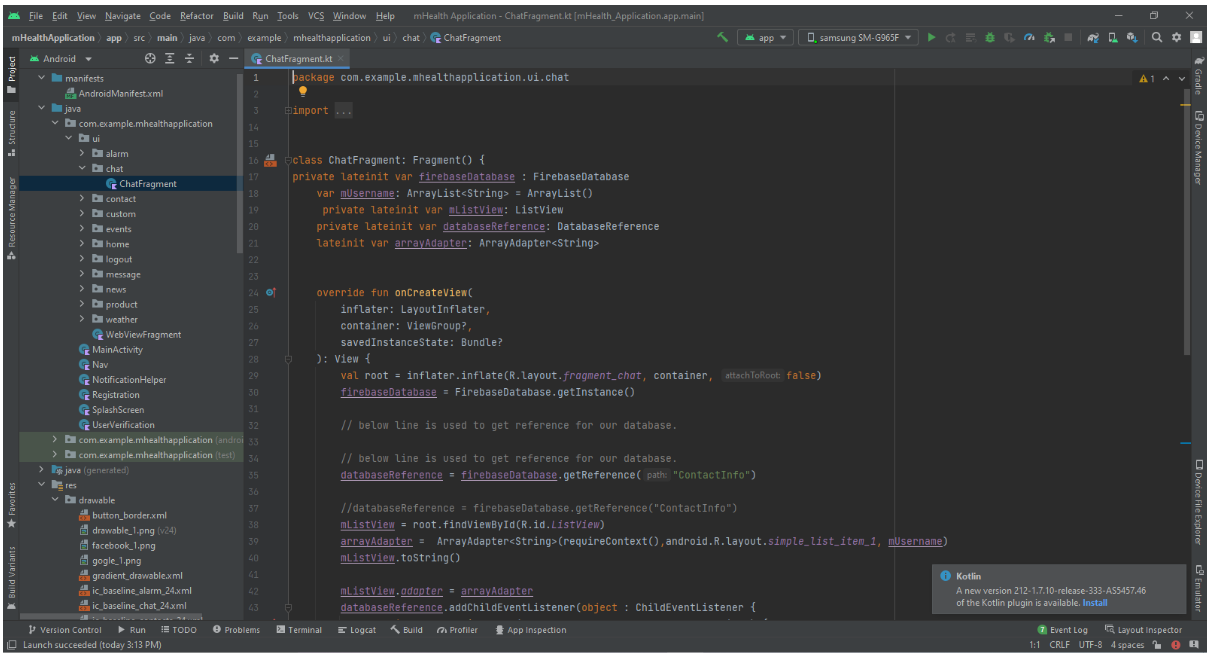


Figure 7.8: Reminder and Notification Back End

The graphical output of the alarm setting, and the reading of messages are shown in Figure 7.9. The message may include system-generated messages or other health-related messages.

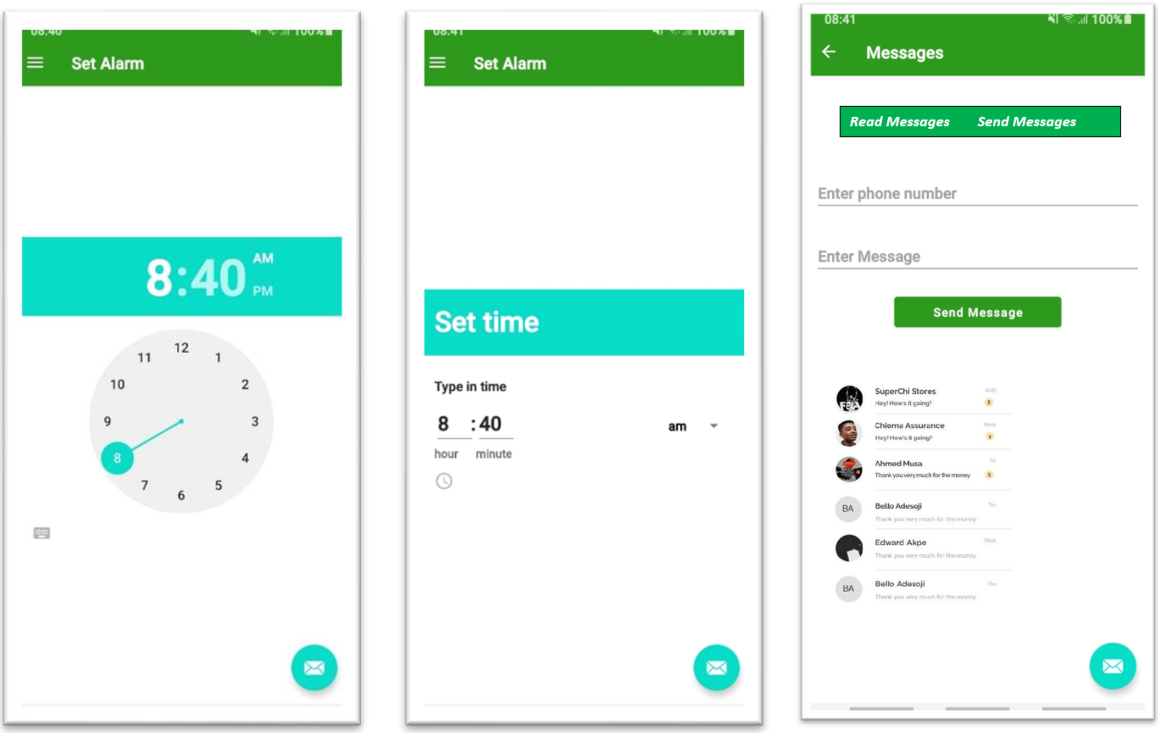


Figure 7.9: Graphical Interfaces of Reminder Settings

After performing the intended tasks, the patient exits the App. The patient clicks the "Exit App" button to exit the application. This function will redirect the patient back to the "Get Started" page of the App. Figures 7.10 and 7.11 demonstrate the front end and the back end of the log-out function; whereas Figure 7.12 demonstrates the graphical interface of the App when the function is invoked.

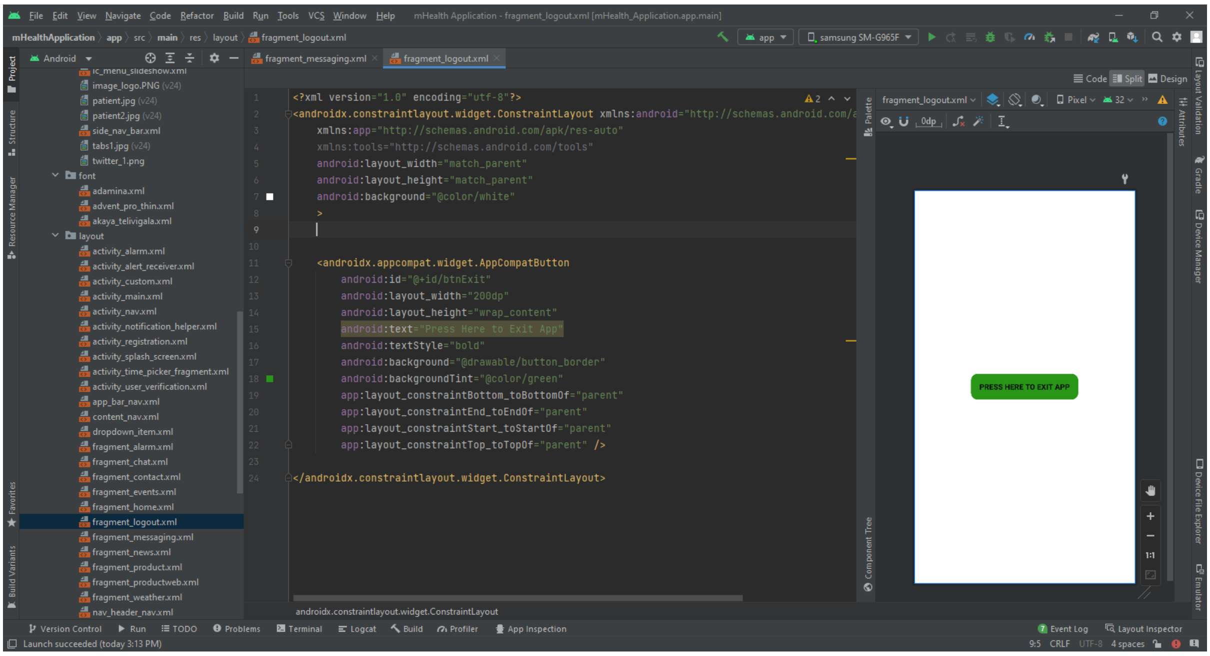


Figure 7.10: Front End of the Logout Function

Logout exits the application, and the patients invoke this functionality when they have finished navigating the system. Figure 7.11 illustrates the back end of the logout function.

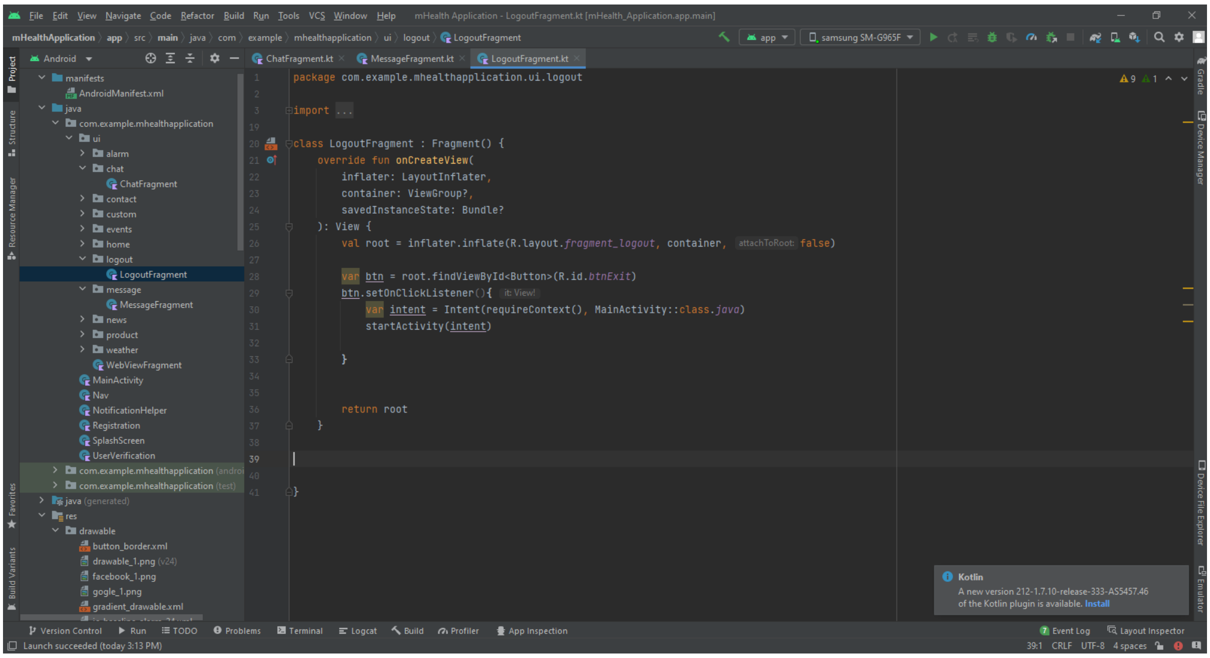


Figure 7.11: Back End of the Logout Function

Only some of the functions of the system are being demonstrated here. However, the mHealth system was designed based on the architecture and the integration processes demonstrated in Figures 6.1 and 7.2, respectively. On completion of the navigation or using the system, the patient or medical professional will exit the application. The graphical output of the logout function is demonstrated in Figure 7.12.

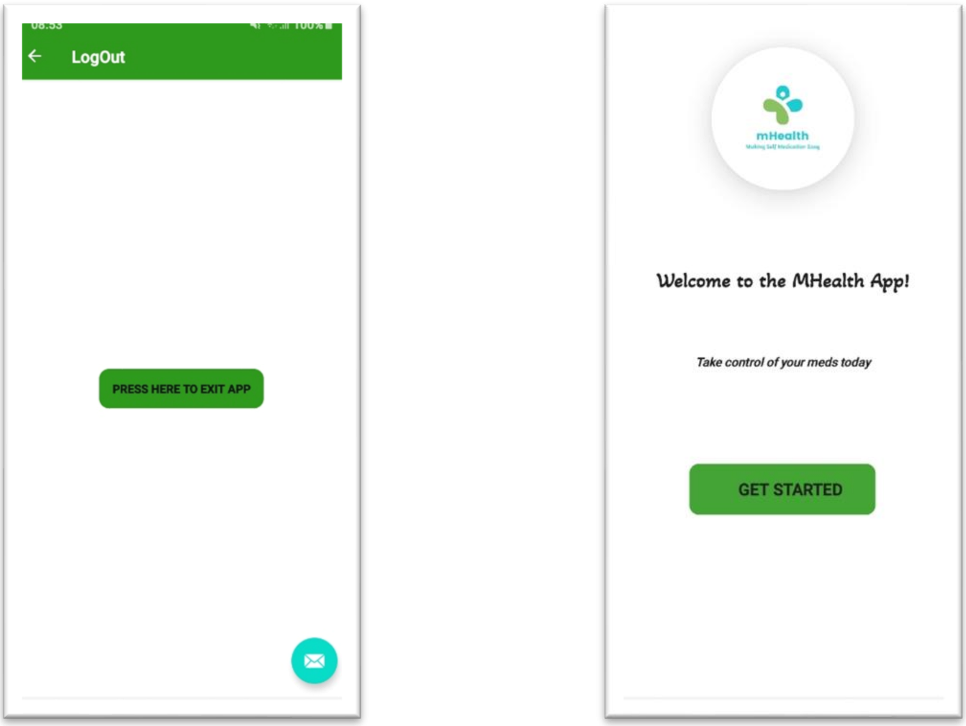


Figure 7.12: Graphical Interface of the Logout Function

7.2.2 System reporting

As demonstrated by Figures 7.2 and 7.3, the system is designed in such a way that a medical professional or healthcare worker may interact with it at their own location and produce a report on the registered patient. These reports form the basis for the evaluation of the patient's reactions to the triggers of the system and the hence responses to drug adherence. The reports also record whether patients interact with the system, and how often this is done. Adherence to medications can also be monitored by observing whether the patient collects the medication at the required time.

7.3 Evaluation of mHealth Self-monitoring System

Design Science Research artifacts may be evaluated using various approaches and methods. These include functional and structural testing, experimental methods - including those conducted in the field and laboratories, statistical analyses, including descriptive and inferential methods, as well as analytical and architectural analysis (Hevner et al., 2007). Depending on the design, various attributes of the artifact may be evaluated. These include checking completeness, functionality, accuracy, reliability, consistency, performance and usability (Peffers et al., 2007; Deng & Ji, 2018). In this study, descriptive analysis was used to analyse expert evaluations of the system.

7.3.1 Design of the evaluation instrument

The artifact was evaluated on the parameters of completeness, functionality, accuracy, reliability, consistency, performance and usability, using a close-ended questionnaire. Each parameter formed a question item of the close-ended questionnaire. The design was based on a 5-point Likert scale in which 1 and 5 represented strongly disagree and agree respectively, 2 and 4 were respective intermediate values, and 3 represented unsure. The evaluation questionnaire is presented in Appendix C.

7.3.2 Population and sampling of experts

The objective of the evaluation was to test whether the mHealth self-monitoring system performed to expectation. This study sought ethics clearance in all the provinces where data was collected. One condition that had to be fulfilled was that no data should be collected from patients. Hence, the evaluation process followed the same instructions of not involving patients. Another requirement was that the artifact had to be placed on the cell phones of the respondents so that they could use it and answer questions for the evaluation process. Due to financial constraints, the evaluation experts were all selected from Gauteng Province. The evaluation data was analysed using descriptive statistics only, therefore a small sample of about 20 respondents was deemed sufficient. A judgment sampling technique was used to select the respondents. Healthcare professionals with relevant expertise working with individuals who have diabetes, including social workers and doctors, were the experts sought. The artifact was set up on the cell phones of these specialists. Participants were requested to practice with it for two weeks. The questionnaire was distributed in person and experts were allowed three days to complete it.

7.3.3 Findings of the evaluation exercise

Respondents were asked to evaluate the artifact based on the seven attributes/functions of the system which included completeness, functionality, accuracy, usefulness, consistency, performance, and usability. The data was collected quantitatively and analysed descriptively, as demonstrated in Table 7.2.

Table 7.2: Descriptive Statistics

	N	Min.	Max.	Mean	Std. Dev.	Variance	Skewedness	
	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	Statistics	Std. Error
Completeness	20	2	5	3.75	1.070	1.145	-.304	.512
Functionality	20	2	5	4.05	.945	.892	-.524	.512
Accuracy	20	2	5	3.70	1.031	1.063	-.282	.512
Usefulness	20	2	5	3.90	.968	.937	-.170	.512
Consistency	20	3	5	4.00	.795	.632	.000	.512
Performance	20	2	5	3.75	1.251	1.566	-.548	.512
Usability	20	2	5	3.55	.999	.997	.024	.512
Valid N (listwise)	20							

The results presented in Table 7.2 demonstrate the respondents' assessment of how the design of the mHealth self-monitoring system complies with the expected criteria in terms of the seven attributes tested. These responses are discussed as follows.

a) **Artifact completeness**: This aspect evaluated whether the artifact's components were sufficiently complete to enable patients and medical personnel to interact with the system, as well as being in a position to receive and share information. Findings indicate that the minimum and maximum responses are 2 and 5; with a mean of 3.75, and standard deviation of 1.070. This implies that most responses were skewed towards agreeing that the system is complete. The graphical skewedness of the respondents' answers to this attribute is depicted in Figure 7.13.

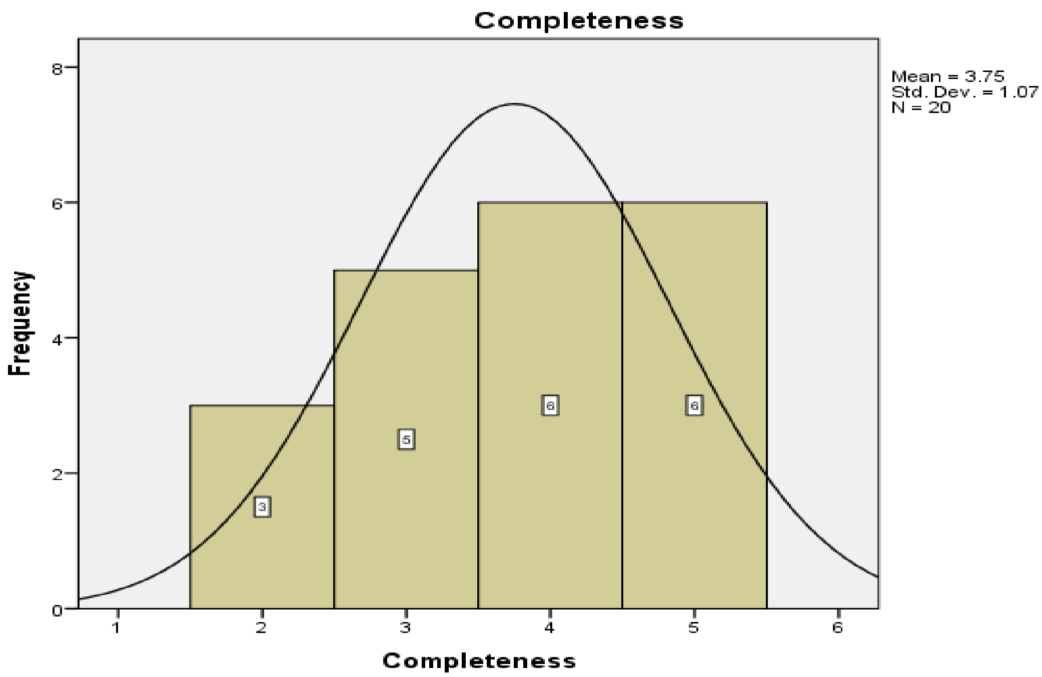


Figure 7.13: Skewedness of the Completeness of the mHealthSM

b) **Functionality**: This aspect referred to the mHealth self-monitoring usefulness, and how well it does in reminding patients to adhere to the medical prescriptions. The system was evaluated for functionality in terms of its input, processing, storage, as well as output, including the extracted reports by the medical personnel. The results shown in Table 7.2 indicate that the responses had a minimum of 2 and a maximum response of 5, with a mean of 4.05 and a standard deviation of 0.945. The implication of these findings is that experts considered the system to be performing averagely as expected.

c) **Accuracy**: This aspect evaluated the effectiveness of the mHealth system in terms of the level of quality and precision, stability and security, and providing solutions without confusion. As demonstrated in Table 7.2, the minimum and maximum responses were 2 and 5 respectively, with a mean of 3.70 and a standard deviation of 1.031. The findings of the study imply that the data for this question was skewed towards agreeing that the mHealth system is accurate. The graphical representation of accuracy of the system is also depicted in Figure 7.14.

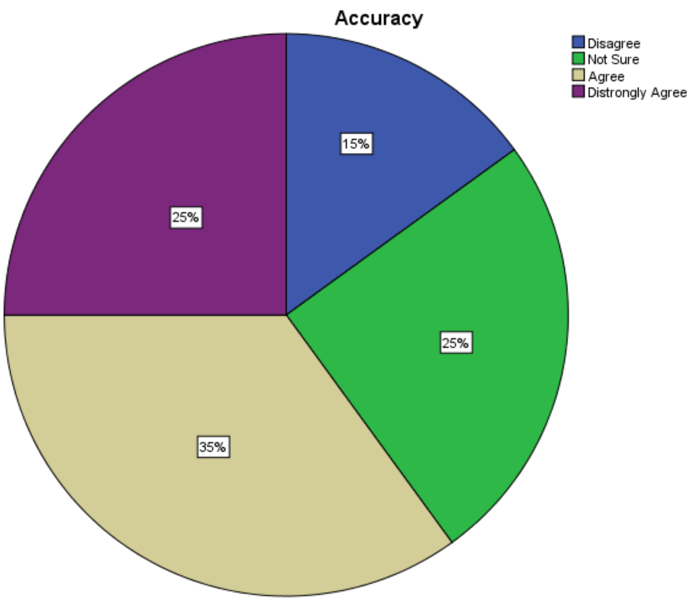


Figure 7.14: Accuracy of mHealthSM

d) **Usefulness**: This aspect assessed the probability that the mHealth self-monitoring system performs correctly regardless of the time and location, and performs adequately according to predefined specifications and requirements, hence it is useful to its intended users. The results shown in Table 7.2 indicate that the experts' responses were skewed toward agreeing that the system is useful and performs according to the stated functional and non-functional requirements.

e) **Consistency**: This aspect evaluated the system's capability to produce a solution as it intended to do. In the case of this study, consistency refers to whether the mHealth self-monitoring system could support patients in self-managing their health. The results shown in Table 7.2 indicate that the expert evaluations were a minimum of 2 and a maximum of 5 with a mean of 3.90 and a standard deviation of 0.968.

f) **Performance**: The system was evaluated in terms of how well it does the reminding of the patients and whether it accurately sends messages as and when needed. The results shown in Table 7.2 indicate that the majority of respondents (n = 14) agreed that the system performs as expected. The performance of the system is graphically represented in Figure 7.15.

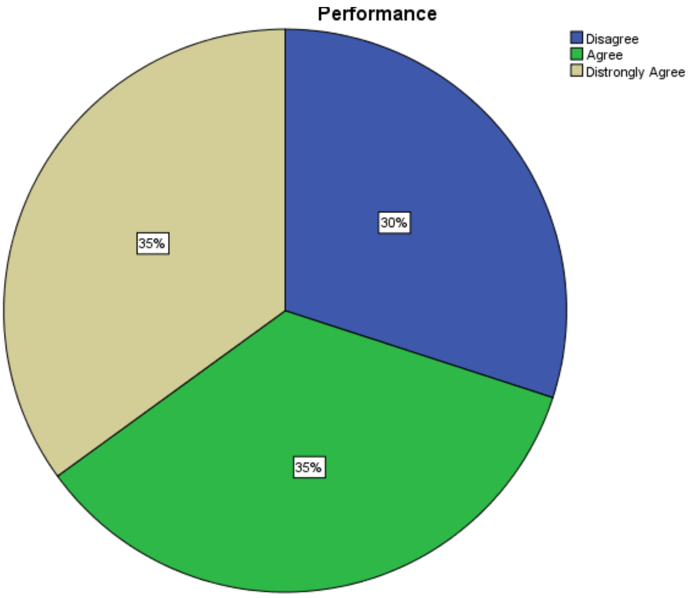


Figure 7.15: mHealthSM System's Performance

g) **Usability:** As demonstrated in Figure 7.2, the mHealthSM system architecture emphasized that the system should be developed incorporating ease-of-use features. This implies that both the patients and healthcare workers should be able to navigate and use the system with ease. The results shown in Table 7.2 indicate that the responses were a minimum of 2 and a maximum of 5, with a mean of 3.55 and a standard deviation of 0.999, with a positive skewedness of 0.024. Therefore, most responses were towards agree and strongly agree. The skewedness of the responses of usability is depicted in Figure 7.16.

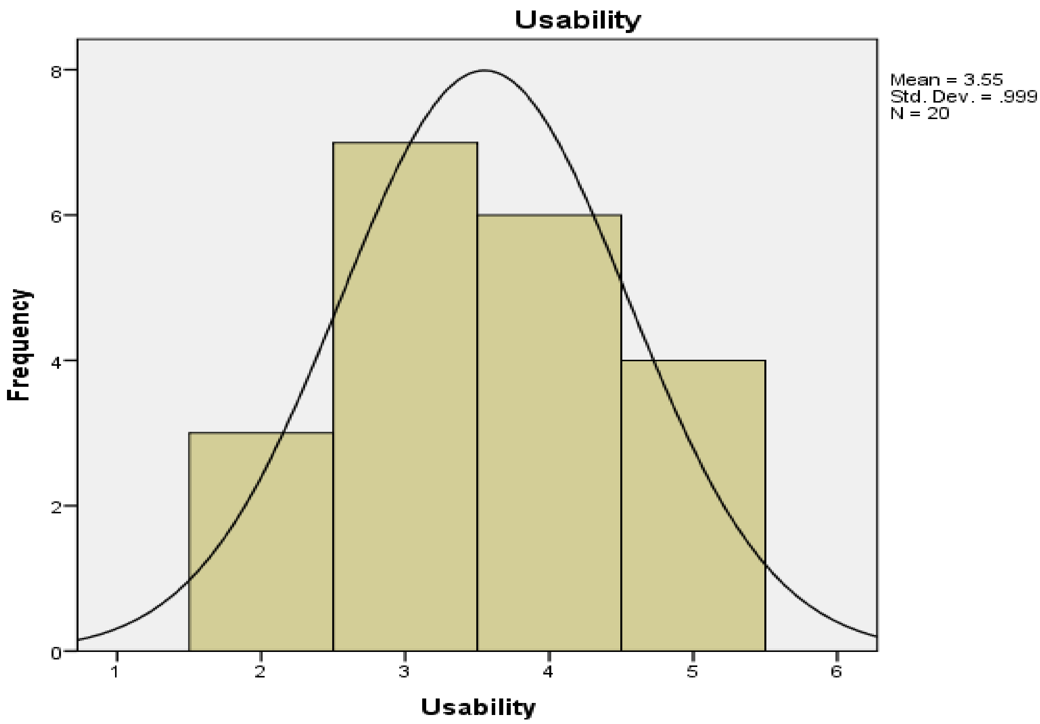


Figure 7.16: Skewedness of Responses Towards Usability of mHealthSM System

7.4 Summary

MHealth self-monitoring may be just as effective as face-to-face consultations and personal visits to healthcare facilities. Not only does the mHealth system play a significant role in shared decision-making, but it is also an appropriate tool for communication with patients undergoing routine treatment. The experiences and lessons learnt after COVID-19 encouraged self-monitoring of mHealth to become an established part of patient care. There was an urgent need to meet remotely with patients with chronic conditions living in far-flung geographical locations (Fekadu et al., 2021; Kendzerska et al., 2021). Diabetic patients, especially those with Type 1 diabetes, find it difficult to regulate their own blood-sugar levels; and this necessitates that they take insulin throughout the day to avoid further complications such as heart and kidney disease, vision and hearing impairment or nerve damage, which in many cases leads to death (Istepanian & Al-anzi, 2018; WHO, 2020).

This chapter presented the designed artifact that can be implemented into a fully-fledged mHealth self-monitoring system to assist those diabetic patients struggling with their glucose management. The designed artifact was evaluated by healthcare personnel in terms of its completeness, functionality, accuracy, reliability, consistency, performance and usability. The results of the evaluation demonstrated that the artifact meets measures that inform self-monitoring in healthcare. The evaluation results also suggest that some functionality of the mHealth self-monitoring system requires an incremental improvement, so as to provide a seamless healthcare support.

CHAPTER 8: CONCLUSION AND RECOMMENDATIONS

The previous chapter presented the development of the mHealth self-monitoring system and the results of its evaluation by the healthcare providers. This chapter offers the conclusion and recommendations of the study. The chapter first gives an overview of the study, lessons learned, as well as the appropriateness of the methodology used to conduct this research. The chapter highlights those aspects that should have been covered by this study, but for certain reasons were not. These are reflected in the limitations of the study and from these recommendations for management and research are given. The chapter ends with a general conclusion of the study.

8.1 Overview of the Study

This study aimed to develop a contextualized model for a persuasive mHealth self-monitoring technology system for diabetic patients in South African communities. The study developed and implemented an artifact for self-monitoring of diabetic patients using persuasive technology. This is in accordance with the WHO's 'global strategy for health for all by the year 2000' which emphasised the eradication of non-communicable diseases such as diabetes (WHO, 2020). According to WHO (2019), preventing NCDs is crucial to enable better healthcare and to reduce long-term care costs while harnessing the potential of economic growth. It is, therefore, vital that better disease-management strategies, systems and innovative tools are implemented to relieve already overburdened healthcare systems, especially in developing countries. In this regard, new tools and integrated care models, such as self-monitoring systems, are required to support primary, community, and home-based healthcare as well as long-term care.

It was notable that the COVID-19 travel restrictions and social distancing reduced access to medical facilities, and aggravated the discrepancies of delivering high-quality healthcare, which resulted in high mortality rates. Fekadu et al. (2021) consider that, due to the experiences of COVID-19, it is important for nations, policymakers as well as researchers to support initiatives intended to keep citizens healthy. It is from this background that governments, policymakers and researchers should embrace innovative activities, systems and awareness programmes that enhance accessibility while improving citizens' willingness to use self-monitoring healthcare systems. Hence mHealth self-monitoring systems have been heralded as an effective tool for fostering physical wellbeing and quality of life among patients (Chifu et al., 2022; Cruz-Ramos et al., 2022). Other possibilities that could also be exploited include assistive technologies for monitoring nutrition and physical activities, awareness campaigns for promoting health, and improving access to healthcare services through digitally accessible, community-based and integrated care models.

As diabetes increases in prevalence around the world, it places a considerable burden on the healthcare systems of countries and patients suffering from these chronic diseases. The rise in diabetes and other chronic diseases is especially challenging for developing countries, as these countries lack adequate equipment and clinics (Chang et al., 2022). Using an mHealth self-monitoring system, patients with diabetes can benefit from enhanced self-care, overcoming the hurdle of resource limitations. Through the use of an mHealth self-monitoring system, patients receiving long-term care will be empowered to play an active role in managing their health and well-being. The system developed by this study has a built-in information search tool that connects to various databases and portals whose information is essential to improve patient health literacy. Patients need to take a more active role in managing their own health.

8.2 Lessons Learned from the Study

Based on the literature reviewed by this study and the study results demonstrated in Tables 5.3, 5.7 and 5.8 and discussed in Chapter 5, several lessons can be learnt about self-monitoring of mHealth for patients suffering from chronic diseases. The results presented in Table 5.9 indicate that all hypotheses proposed that linked to environmental aspects, technological characteristics, individual characteristics due to attitude and beliefs, as well as mobile technology were accepted. On the other hand, hypotheses concerning social aspects, individual characteristics due to skills and culture, were rejected. Since mHealth systems are generally delivered through smartphones, environmental barriers are not very problematic. In most countries today, including developing countries, there is an ever increasing rate of penetration of telephony, which makes mobile phone-based applications a good medium for health monitoring regardless of the patient's location (Asongu & Odhiambo, 2018; Hawthrone & Grzybowksi, 2019).

The mHealth self-monitoring system architecture presented in Figure 7.2 indicated that the system should be developed with ease-of-use features. These two technological characteristics − the ease of use and usefulness of the system, are universally accepted as being essential. Diabetic conditions are prevalent amongst both youth and adults, therefore, the mHealth self-monitoring system should be accessible to all age groups in such a way that they are easy to use and at the same time, patients should appreciate its usefulness. As Jia et al. (2015) remind us, failure to make an mHealth system easy to use will mean that it is only accessible to and used by patients who are younger, while the elderly will be socially isolated.

Since many other complications of the disease exist in addition to chronic diseases, positive social support is considered to be an essential aspect of life for patients and improves positive motivation and enthusiasm, leading to a better human experience on the path to recovery. Social support may increase resilience to stress, hence lessening the effects of trauma and depression (WHO, 2020; Fogg, 2020). However, in patients with chronic diseases, this social support may not be applicable. Patients with chronic diseases are more comfortable and open to their healthcare personnel than to their relatives or peers. The stigmatization of having an incurable health condition makes these patients reserved and sometimes leads to low self-esteem (Kalema & Mosoma, 2019; Meier et al., 2020). This implies that healthcare personnel must design programs that focus on building the capacity of individual patients, as well as their family members, to effectively manage chronic disease, including controls and taking care of their loved ones.

8.3 Appropriateness of the Methodology Used for this Study

The epistemological stance of this study was that, to understand more about mHealth self-monitoring, this study had to familiarise itself with how healthcare personnel perceive patient behaviour with respect to medical adherence. From this viewpoint, the triangulation of methods of quantitative and the Design Science methodology was seen to be appropriate, and this combination has also been suggested by the related studies in the literature. The quantitative approach was used to analyse the perceptions of healthcare personnel that led to the development of the model, while DSR was appropriate to give the true sense of self-monitoring, by developing an artifact for mHealth (Deng & Ji, 2018). It was also envisaged that, since patients with chronic conditions may isolate themselves from their peers, an online system that could connect them with healthcare workers or patients with similar conditions would be appropriate for their support. Designing an mHealth self-monitoring reminder system with tools that provide alerts and reports was thought to be a good solution for diabetic patients who require medication adherence to avoid severe complications that could lead to death (Shaw et al., 2020; Chang et al., 2022).

The FBM indicates that sufficient motivation, ability and effective triggers are essential antecedents in human response to stimuli (Fogg, 2009). This implies that before the actual use of an mHealthSM system will occur, behavioural change should be a mediator factor, as was demonstrated in the conceptual model in Figure 3.1. The model also indicated that certain factors that acted as triggers were impacted by the environmental aspects. This led to the design of a 3-stage model whose analysis using linear regression would have been complex. Another consideration was the interacting effects of the moderating factors on the influence of the independent variables on the mediating variable and on the influence of the mediating variable on the dependent variable. Therefore, for the simplified multivariate analysis of the 3-stage conceptual model with interacting effects, Smart-PLS was thought to be appropriate for giving a covariance-based SEM (Ringle et al., 2022). The Smart-PLS SEM was deemed appropriate for this study due to its flexibility in normality and sample size. This study analysed 158 datasets and that was below the recommended 200 for covariance-based SEM (Ringle et al., 2022).

8.4 Limitations of the Study

The following are the limitations of the study,

a) This study sought to develop a contextualized model for a persuasive technology mHealth self-monitoring system for diabetic patients in South African communities. This implies that this study intended to model the psychological characteristics of diabetic patients that influence the behaviour to use mHealth self-monitoring systems. Although data was collected in three South African provinces to ensure contextualization, and the study followed a quantitative approach where data was collected using simple random sampling to allow generalization, due to ethical restrictions, only healthcare personnel participated in the data collection rather than the patients. Careful effort was made to design the questionnaire items to meet both content and construct validity, and efforts were made to screen the data to remove outliers, but the findings of this study must be adopted with care as they may lack generalisation to patients.
b) The use of persuasive technology to cause a change in behaviour involves the incorporation of technological aspects of mobile technology software and hardware, together with the individual characteristics of the users and other factors such as environment, institutional support, and social and cultural aspects. This study revealed that the demographics and situational variables of the patients moderate the influence of these independent variables on behaviour. However, while the study only collected data for analysis at one time (a snapshot), patients' behaviour may be modified over time as they continue to use the persuasive technology (Fogg, 2009; Kalema & Mosoma, 2019; Chang et al., 2022). This implies that, with continued usage of the self-monitoring system, some factors used in the model might cease to be significant, while others become salient.
c) Increasing globalization and urbanization are causing several chronic diseases, both communicable and non-communicable, to become more prevalent (Matseke, 2023; WHO, 2019). As the number of people with chronic diseases increases, healthcare systems become overwhelmed with the many patients who require routine care. Technological innovations, such as self-monitoring of mHealth, become key in improving the self-management of patients' health. The mHealth self-monitoring system developed for this study goes beyond simply providing health information and SMSs to include a reminder system and printing the patient's interaction reports. The reminder system was developed in such a way that the times for the alarm to sound and the sending of messages are set manually by the patient or a

healthcare worker. This implies that the system is not intelligent enough to detect the patient's condition before the alarm or reminder sounds.

d) This study concerned itself with the development of a self-monitoring system for medicine adherence by diabetic patients only. There was no intervention to influence health outcomes. This study acknowledges that there are several other ways in which diabetic patients can be monitored, such as the rate of their physical activity, weight gain or loss, and blood glucose levels. These other health monitoring interventions were beyond the scope of this study even though they play a critical role is the self-monitoring of diabetes.

8.5 Recommendations of the Study

Self-monitoring for chronic diseases including diabetes has traditionally been performed with the maintenance of paper-based diaries. The use of technological innovations like mHealth could reduce the burden of self-monitoring and provide feedback to enhance adherence. Daily reminder messages delivered by the system are essential in improving adherence as a way to improve diabetic conditions. Results of the study confirmed that adherence due to self-monitoring is associated with behavioural changes that are triggered by the mHealth self-monitoring system. Hence, there is a need for more studies in this direction. This study represents a preliminary step in the use of mobile technology in diabetes self-monitoring efforts. Literature indicates that a growing body of research has investigated mHealth interventions for the self-management of diabetes world-wide, with most conducted in the Western settings. Most of this research supports the view that mHealth interventions are a promising means to promote behavioural changes among patients with chronic diseases by providing them with real-time reminders to take their medicine, and also enabling them to access information, feedback and social support. Future research should carryout rigorous and innovative study designs and intervention strategies that include voice input and output for patients with visual impairments.

8.5.1 Recommendation for future research

The limitations of the study have indicated issues that were not anticipated during the research planning. These may be resolved in future research that this study recommends. Among the recommendations are:

a) The restriction that did not allow data to be collected from patients led to data being collected from medical practitioners and healthcare workers only. This study recommends that future research should endeavour to collaborate with the health departments so that data is collected from patients, thus increasing both the validity and reliability of the findings. This will also necessitate careful ethical considerations at all levels of research in terms of data collection, analysis and disposal, as well as the triangulation of methods to include qualitative analysis of patients' responses.

b) After the initial technology acceptance, the post-adoption is influenced by the users' behavioural change due to their satisfaction or dissatisfaction and as such is paramount for continuance usage (Ramos, 2022). Continuance usage of technology is influenced by several factors, among them are the perceived ease of use, conformation of use, expected pressure, trust and satisfactions that influence intention to continue usage (Mahakhant & Rotchanakitumnuai, 2021). Therefor this study recommends that, since there is a likelihood that patients perception towards the mHealth self-monitoring system might change with time, data collections should be done at different times as some triggers may become insignificant, whereas others become salient. It is recommended that future research should use longitudinal data collection in which data is collected at different intervals after usage. This will help to identify those factors that have ceased to be significant, together with those that have become salient.

c) Among the risk factors of diabetes are rate of physical activity, weight gain or loss, and blood glucose levels (Ekholuenetale et al., 2023; Mbogori & Mucherah, 2019). There is a need to design an integrative mHealth self-monitoring system that could monitor all or some of these health conditions that should be monitored, into one integrated system, however this has been a limitation for many other studies including the current one (Debon et al., 2019). Furthermore, due to the increasing number of patients suffering from chronic diseases, data storage, as well as network stability, can become an impediment to the effective use of the mHealth self-monitoring system. Therefore, this study recommends that future research should design an integrated mHealth self-monitoring system that should be supported by a cloud-based system. Cloud-based solutions will provide various benefits, including stability, availability, and security, in addition to healthcare personnel now being in a position to analyse patients' data from a central platform.

8.5.2 Implication for practice

Result of this study concurred that mHealth interventions are comparable to or better than traditional healthcare for diabetic patients. In general, mHealth self-monitoring improves the quality of life of patients and their families and significantly contributes to their satisfaction. It is of paramount importance that mHealth is used and also improved to continue playing the palliative and supportive care of not only diabetic patients but all patients with chronic conditions. This study makes the following recommendations to practice.

a) This study recommends that future research develops mHealth self-monitoring that is intelligent enough to automatically collect patient data and transmit it to the mobile device through messages. These messages should be both text and audio to include patients with physical impairment. Furthermore, patient data should be displayed on the site of healthcare personnel to allow printing of the evaluation report. These types of collected data should also be available and accessible by the patients at any time, from anywhere, through electronic storage. This will help to ease the work of the healthcare personnel due to the increasing number of patients suffering from diabetic complications.
b) The mHealth self-monitoring system holds a potential to provide automated, tailored support for treatment adherence among diabetic patients. Yet due to many medical restrictions relatively few academic non-clinical research trials have guided its development and patients who are the intended end-users are infrequently involved in the design process. Most systems features or functions are based on known software engineering non-functional requirements, and this limits the best-fit that would suit patients' needs well. There is a need for collaborative research that would involve researchers, developers, patients and healthcare workers as well as psychologists and behavioural scientists in order to come up with a more comprehensive integrative system.

8.6 Conclusion

Over the past few decades, the health sector has undergone constant disruption, evolution, and transformation. Certainly, the dynamism of this industry will not decline soon, since human healthcare demands will continue to increase over time. As healthcare administration prepares itself for new challenges, it will remain critical to provide excellent and easily accessible healthcare facilities. Globally, there is a growing trend towards computerisation of healthcare in the hope of improving health outcomes, reducing costs for both healthcare providers and patients, as well as improving the ease of access to data and the sharing of healthcare information (Abduo et al., 2020; Umaefulam et al., 2022). On the same note, the COVID-19 experiences made it clear that, should technological innovations be effectively and efficiently used for healthcare, the number of patients visiting doctors will drop dramatically and this will reduce the weight placed on the healthcare systems of countries (Fekadu et al., 2021).

Computerization of healthcare not only helps in the sharing of medical information and communication with patients, but also helps to provide accurate diagnoses and to empower patients to take care of their own lives (Abduo et al., 2020; Kruse et al., 2019). The management of patients' own lives is essential, as it helps them remain healthy and minimises readmissions to hospitals, thus reducing health-related costs and improving their quality of life (Chatterjee, 2019; Chifu et al., 2022). With the expected increasing number of world pandemics, it is no longer optional that healthcare moves towards real-time data analytics to improve timely decision-making related to the saving of lives. In doing so, more technological interventions in healthcare and management are needed to stay in touch with the increasing globalisation in the Fourth Industrial Revolution (4IR) era.

The widespread use of technological innovations in the healthcare domain, and the increase in disease burdens, have made mHealth a highly sought-after tool in the health sectors of many countries, developing or developing. MHealth has been widely applied in the different aspects of healthcare management, especially with chronic complications that require routine monitoring, making adherence a challenge (Moses et al., 2021). MHealth systems, such as the one developed in this study, not only work as a reminder system for patients but also allow healthcare professionals to collect quantitative information related to patients’ health and behaviour towards medicine adherence and this helps healthcare personnel to make meaningful decisions. Through the data generated, stored, and disseminated by mHealth systems, healthcare providers will be able to collect patient-related data and make decisions such as patient risk prediction, need for physical monitoring, or admission to intensive care. On the other hand, the integration of patients’ electronic health records, their behaviour and use of wearable technologies through the use of mHealth self-monitoring is essential for patient self-monitoring of their chronic conditions. Furthermore, an understanding of how to use the data generated from patients suffering from chronic conditions, such as diabetes, could lead to better treatment, as well as effective monitoring and control of related complications that may arise from worsened conditions of chronic diseases due to poor adherence to medicine (Shaw et al., 2020).

Through the use of a close-ended questionnaire, this study gathered information from various healthcare personnel who interact with diabetic patients. The collected data were analysed using Smart-PLS SEM to develop a model for mHealthSM. Based on the developed model, an mHealth system architecture was designed. The artifact informed the integration of patients’ behaviour into mobile technologies while linking to the patients’ electronic healthcare records. As demonstrated in this study, it could be deduced that, with the ubiquitous adoption of smartphones across racial, educational, and socio-economic groups, it is possible to develop new models of healthcare delivery for patients with chronic conditions, such as diabetes, to promote health and equity. Healthcare management through mHealth self-monitoring systems can help improve medication management. Their reminder system could lead to patients’ hospital readmissions being minimized, thus reducing healthcare costs (Chang et al., 2022). It is, therefore, vital that patients receive timely reminders to take their medicines at the right time and in the right quantity (for instance, to avoid overdosing) and that their prescriptions are renewed on time.

Lastly, mHealth self-monitoring systems might benefit pharmaceutical companies as well, since they may reduce the cost of clinical trials, thereby enabling these companies to provide more accurate information about medicines and the production of new drugs. In this case, the goal is to ensure that the specific medicine works and to gain insight into individual patients reactions to the medication so that healthcare can be optimized. Additionally, physicians can tailor treatment plans for patients based on the same information as that generated from the mHealth system. Self-monitoring is key to adherence, and this helps to reduce healthcare costs and waste of medicine. It is, therefore, imperative that patients and physicians work together to tailor treatment plans in order to reduce healthcare-related costs. Empowering patients to gain control and to participate in their own health, is the better way to go, as the world strives to eradicate disease, poverty, and to improve health equity and equality.

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APPENDICES

Appendix A: Ethics Approval

UNISA university of south africa

UNISA-CAES HEALTH RESEARCH ETHICS COMMITTEE

Date: 06/06/2022

NHREC Registration # : REC-170616-051
REC Reference # : 2022/CAES_HREC/105
Name : Ms MR Kgasi
Student #: 10151133

Dear Ms Kgasi

Decision: Ethics Approval from 02/06/2022 to 31/05/2027

Researcher(s): Ms MR Kgasi
10151133@mylife.unisa.ac.za; 071-563-2737

Supervisor (s): Dr L Motsi
motsil@unisa.ac.za; 011-670-9426

Prof B Chimbo
chimbb@unisa.ac.za; 011-670-9105

Working title of research:

A contextualized model for a persuasive technology mobile health self-monitoring system for diabetic patients in rural South African communities

Qualification: PhD Information Systems

Thank you for the application for research ethics clearance by the Unisa-CAES Health Research Ethics Committee for the above mentioned research. Ethics approval is granted for five years, **subject to further clarification, and submission of the relevant permission letters and yearly progress reports. Failure to submit the progress report will lead to withdrawal of the ethics clearance until the report has been submitted.**

The researcher is cautioned to adhere to the Unisa protocols for research during Covid-19.

Due date for progress report: 31 May 2023

The progress report is available on the college ethics webpage: https://w2.unisa.ac.za/www.unisa.ac.za/sites/corporate/default/Colleges/Agriculture-%26-Environmental-Sciences/Research/Research-Ethics.html

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Please note the points below for further action:

1. The committee notes that permission will be obtained from the relevant provincial departments of health once ethics clearance has been given; please note that these letters must be obtained and submitted to the committee before data collection may commence.
2. The title and objectives create the impression that diabetic patients will be included in the research, which is not the case. The committee recommends that the title and objectives be amended to reflect that the research will focus on the health workers' perceptions.
3. Will the research not benefit from including diabetic patients as well? Should the researcher consider doing so, please provide the methodology that will be followed to identify and approach these respondents.
4. The committee recommends that a question be included in the questionnaire to record the occupation of the respondent (e.g. doctor, nurse, etc.)
5. Please use the latest consent form provided on the college ethics webpage, as the form used still contains the name and details of a former Chair of the committee.
6. Please ensure that the questionnaire appears professional before distributing it; it should reflect the Unisa logo etc.
7. The committee commends the researcher for the detailed and thorough application.

*The **low risk application** was **reviewed** by the UNISA-CAES Health Research Ethics Committee on 02 June 2022 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:

1. The researcher will ensure that the research project adheres to the relevant guidelines set out in the Unisa Covid-19 position statement on research ethics attached.
2. The researcher(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
3. 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 Committee.
4. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.

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5. 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.
6. 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.
7. 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.
8. No field work activities may continue after the expiry date. Submission of a completed research ethics progress report will constitute an application for renewal of Ethics Research Committee approval.

Note:

*The reference number **2022/CAES_HREC/105** should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.*

Yours sincerely,

Prof MA Antwi
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Appendix B : Main Survey Questionnaire

A Contextualized Model for a Persuasive Technology Mobile Health Self-Monitoring System for Diabetic Patients in South African Communities

This questionnaire consists of two sections.

Section A: Participants demographics and situation variables

Section B: Participants perceptions towards mHealth Self-monitoring system use

In this study:

A mobile health monitoring system is a mobile computing application that improves communication between health care workers, physicians, and patients in order to deliver better health care.

SECTION A: PARTICIPANTS DEMOGRAPHICS

Please select an alternative that corresponds to the choice of your answer to the question.

1. What is your age group?

d)

e) 20 years and below		g) 21-30 years		i) 31-40 years		k) 41 - 50 years		m) 51 years and above	r

o)

2. What is your Gender?

Male		Female	

3. What is your overall working experience?

0-5 years		6-10 years		11-15 years		16 -20 years		21-25 years		26 years and above	

4. What is your working position/occupation?

Health worker		Nurse		Doctor		Teaching consultant	

5. I am aware of Mobile health monitoring systems

YES		NO	

SECTION B:

Using the rating scale from 1-5 where ***1 = strongly disagree, 2 =Disagree, 3 = Neutral, 4= Agree, 5 = strongly agree*** please indicate your level of agreement or disagreement on the following statements.

Mobile health technology (is defined as mobile computing, medical sensors and communications technologies for healthcare.)	1	2	3	4	5

1	I expect mobile health technology to be easy to use by patients					
2	I expect mobile health technology to be scalable enough to accommodate various features					
3	I expect mHealth monitoring system to motivate behavioural change and also act as a support system towards such change					
4	I believe mHealth built on persuasive technology will change patients' behaviour to adhere to medicine					
Environmental Factors (is defined as surrounding factors in the patients' environment)		1	2	3	4	5
5	I believe the network is available to people to use mHealth system					
6	I believe that the SA government has policies that support the use of IT					
7	I believe people will be able to afford the mHealth system					
8	I believe that infrastructure resources exist to support the use of the mHealth system.					
9	I believe there is educational support for people who do not know how to use mHealth systems					
Culture (refers to the attitudes, behaviour, values and norms of certain social group or society)		1	2	3	4	5
10	I believe patients' culture may have an influence on their acceptance and use of mHealth					
11	The communities and environments in which people live may have an impact on how they use technological innovations.					
12	The medical community's culture may prevent them from supporting the adoption of an mHealth monitoring system.					
Individual Characteristics (refers to the patients' attitudes, beliefs and skills that influences their use of technology)						
p) a) **Patient's attitude (**It refers to the manner in which one is thinking, feeling, or behaving which shows his opinion) q)		1	2	3	4	5
13	I believe patients will have a positive attitude towards mHealth self-monitoring system					
14	I expect medical personnel and social workers to embrace mHealth self-monitoring system					
15	I believe the mHealth self-monitoring system will increase patients' drug adherence					

16	I believe that the frequent use of an mHealth system will help patients eventually to remember their medication schedule even in the absence of such a device					
b) Patients' Beliefs (refers to the personal thinking or perception of a patient relating to a particular system or medical professionals**)**		1	2	3	4	5
17	Patients believe that monitoring their health is rewarding.					
18	Many patients will prefer their health to be monitored by the mHealth self-monitoring system than social workers.					
19	The possibility of patients resisting the mHealth system may be lower than expected					
c) Patients' Skills (refers to the personal capability and preparedness of a patient to use a technological innovation**)**		1	2	3	4	5
20	Patients do have enough and relevant skills to use the self-monitoring mHealth system					
21	Many patients' education background is strong enough to use mHealth					
22	With support, I believe patients' will be able to use technology to self-monitor their health					
Performance Expectancy (this refers to the degree at which mHealth is perceived as providing greater benefits in the improvement of patients' health)		1	2	3	4	5
23	Patients will find mHealth self-monitoring system useful in their daily life					
24	Using mHealth self-monitoring system will increase patients' chances of managing health					
25	Using mHealth self-monitoring system helps will help patients to adhere to medicine prescriptions					
Effort Expectancy (is the degree to mobile banking is perceived as being consistent with the existing values, past experiences, and needs of potential adopters)		1	2	3	4	5
26	Learning how to use mHealth self-monitoring system will be easy for patients					
27	Patients' interaction with mHealth self-monitoring system will be clear and understandable					
28	Patients will find mHealth self-monitoring system easy to use					
29	It will be easy for patients to become skillful at using mHealth self-monitoring system					

		1	2	3	4	5
Social Influence (this refers to a behaviour shared by a group of people who also share the same norms and values**)**		1	2	3	4	5
30	I believe close relatives, family members, and friends will offer their support towards patients' use of the mHealth self-monitoring system					
31	It is more likely that patients will use mHealth self-monitoring system if they know of others using it					
32	I believe medical personnel and patients will be keen to learn about mHealth self-monitoring system					
Facilitating Conditions (this refers to support expected by patients from the healthcare providers)		1	2	3	4	5
33	Patients have the resources necessary to use mHealth self-monitoring system					
34	Health institutions are in a position to facilitate patients with the knowledge needed to use mHealth self-monitoring system					
35	Patients can get help from others when they have difficulties using mHealth self-monitoring system					
behavioural intention (refers to those motivational factors which captures how hard people are willing to try to perform a behaviour and intentions are said to be the most influential predictor of a behaviour**)**		1	2	3	4	5
36	Patients will tend to use the mHealth self-monitoring system					
37	Health institutions intend to support the use of mHealth self-monitoring system					
38	Health institutions will recommend patients with diabetic condition to use mHealth self-monitoring system					

Overall patient's monitoring (This is the expected effectiveness of the mHealth towards monitoring patients based on their other internet-based usage**).**

Please range the expected usage of these services by diabetic patients that could influence their use of mHealth self-monitoring system for monitoring drug adherence

		Never	Less often	Often	Once a day	Many times, per day
39	SMS					
40	WhatsApp					

42	Mobile e-mail					

END – THANK YOU

Appendix C : Expert Artifact Evaluation Questionnaire

Dear respondents,

Kindly provide your evaluation of the artifact of persuasive technology mobile health self-monitoring system for diabetic patients in south African communities. This evaluation process is assessing seven attributes of the artifact. These are completeness, functionality, accuracy,

Your participation is much appreciated.

Thank you.

Please make a cross (**X**) to the cell that best describes your evaluation of the artifact according to the given attributes.

(1= Strongly disagree, 2 = Disagree, 3 = Not Sure, 4 = Agree, 5 = Strongly Agree)

Artifact Attribute	1	2	3	4	5
Completeness of the Artifact: The features and dimensions of the artifact follows a logical flow and are complete enough to be used for mHealth self-monitoring by diabetic patients.					
Functionality of the Artifact: I am satisfied with the functioning of the artifact to be used as a reminder for patients to take their medicine					
Accuracy: The artifact as a reminding system performs accurately by giving reminders on time.					
Reliability: The artifact can reliably be depended on by both healthcare providers and patients to remind patients to adhere to medicine.					
Consistency: The artifact gives consistent reminders to patients and feedback to healthcare providers about patients adherence to medicine.					
Performance: The artifact performs to the expectation that it can empower patients to take care of their lives					
Usability: I believe that both patients and healthcare providers can navigate the artifact with ease and use it to set reminders and reports generation					

THANK YOU

Appendix D : Permission Letters to Collect Data

health
Department:
Health
North West Provincial Government
REPUBLIC OF SOUTH AFRICA

2030 NDP

1st Floor, Health Office Park
Private Bag X 2068
MMABATHO
2735

RESEARCH, MONITORING & EVALUATION

Tel: +27 (18) 391 4501
Email: MbuleloT@nwpg.gov.za
www.nwhealth.gov.za

HEAD OF DEPARTMENT
2022 -09- 07
NORTH WEST DEPARTMENT OF HEALTH
PRIVATE BAG X 2068, MMABATHO, 2735

Name of Researcher: **Ms M. Kgasi**
Tshwane University of Technology

Physical Address: ______________________
(Work/ Institution) ______________________

Subject: **Research Approval Letter – A Contextualized Model for a Persuasive Technology Mobile Health Self-Monitoring System for Diabetic Patients in Rural South African Communities.**

This letter serves to inform the Researcher that permission to undertake the above mentioned study has been granted by the North West Department of Health. The Researcher must arrange in advance a courtesy meeting with the District Chief Director and the Chairperson of the District Health Research Committee (DHRC) (as per their details below), to introduce their research team/members on the proposed research to be undertaken. The researcher can thereafter proceed to the identified institution/s and/or facility and produce this letter to the Management as proof that the research was approved by the NWDoH.

This letter of permission should be signed and a copy returned to the department. By signing, the Researcher agrees, binds him/herself and undertakes to furnish the Department with an electronic copy of the final research report. Alternatively, the Researcher can also provide the Department with an electronic summary highlighting recommendations that will assist the Department in its planning to improve some of its services where possible. Through this, the Researcher will not only contribute to the academic body of knowledge but also contributes towards the bettering of health care services and thus the overall health of citizens in the North West Province.

Below are the contact details.

Office of the Chief Director: Bojanala District	Chairperson of the DHRC
Dr K. Segwai	Prof. J. Tumbo
Contact person: Goitsemang Khumalo	**Contact person:** Obakeng Masango
014 592 8906 KhumaloG@nwpg.gov.za	014 592 8906 NMasango@nwpg.gov.za

Kindest regards,

Dr. FRM Reichel
Director: RM&E

Date: 7/9/2022

Researcher

Date: ____________

GAUTENG PROVINCE
HEALTH
REPUBLIC OF SOUTH AFRICA

Annexure 1

Declaration of intent from the clinic manager or hospital CEO

I give preliminary permission **Mmamolefe Rosinah Kgasi** to do his or her

research on **a contextualized model for a persuasive technology mobile health self-monitoring system for diabetic patients in rural South African communities** in

________________________ (name of clinic) or

________________________ (name of CHC) or

Jubilee District Hospital
________________________ (name of hospital).

I know that the final approval will be from the Tshwane Regional Research Committee and that this is only to indicate that the clinic/hospital is willing to assist.

Other comments or conditions prescribed by the clinic or CHC manager or hospital CEO:

____
Signature
Clinic Manager/CHC Manager/CEO

06.09.2022
____
Date

MPUMALANGA PROVINCIAL GOVERNMENT

health
MPUMALANGA PROVINCE
REPUBLIC OF SOUTH AFRICA

WITBANK HOSPITAL

Witbank Hospital,Mandela Avenue,Emalahleni,Mpumalanga
Private BagX11285,Mbombela,1200,Mpumalange Province
Tel:013 653 2000, Fax:013 656 1314

Litiko Letemphilo | Departement van Gesondheid | UmNyango WezeMaphilo

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Enquiries: Ms B.P Phiri
Tel: 072 321 2098

TO: Mmamolefe Kgasi
Lecturer Tshwane University of technology

FROM: Mrs K.A.P Madonsela
Chief Executive Officer
Witbank Hospital

DATE: 25/08/2022

RE- REQUEST FOR PERMMISSION TO CONDUCT RESEARCH AT WITBANK HOSPITAL.

We are pleased to inform you that we approve your request to conduct your academic research in the institution on a contextualized model for a persuasive technology mobile health self-monitoring system for diabetic patients in rural south African communities.

This is a factor that needs to be unveiled to better the wellbeing of our Diabetic Patients in the Country.

We will support you throughout the execution.

Regards

pp [signature]
Mrs K.A.P Madonsela
CEO Witbank Hospital

25/08/2022
Date