RELATIONSHIP BETWEEN STUDENT AND SUPERVISOR FIT, AND 'TIME TO COMPLETION' IN MASTERS AND DOCTORAL PROGRAMMES

by

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Relationship between student and supervisor fit, and 'time to completion' in masters and doctoral programmes

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.

I further declare that I submitted the thesis to originality checking software and that it falls within the accepted requirements for originality.

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

Signature　　　　　　　　　　Date

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Abstract

The higher education sector has become increasingly concerned with the efficient use of public resources, as well as improving the research capacity within the country to grow the knowledge economy. As such, there has been an increased focus on master's and doctoral education to ensure that students complete their qualifications timeously. This both increases the knowledge economy, as well as the potential supervision capacity to ensure sustainable growth in the sector. One of the most influential factors relating to master's and doctoral qualification completion according to literature is students' relationships with their supervisors. This study investigates whether supervision relationships influence students' time to completion in master's and doctoral education.

The investigation was conducted at the University of South Africa, an Open Distance e-Learning institution. The study utilises correlational design, and is based on the concept of supervision styles as described in the work of Gatfield (2005). Supervision is viewed as a combination of two factors, namely: structure and support. Measurements of supervision style preferences of students and supervisors are developed based on this theoretical foundation, and distributed to students and supervisors as part of a cross-sectional online survey.

The data collected from the students are analysed through confirmatory and exploratory factor analysis techniques. A valid and reliable factor structure is identified in the data analysis, which reflects the two-factor structure envisioned in Gatfield's (2005) theoretical framework.

The data analysis reveal that master's and doctoral students shared similar supervision style preferences. Furthermore, supervisors who were more involved in their students' work tended to prefer more structured and supportive relationships. In contrast to the initial assumptions made within this project, congruence between the supervision style preferences of students and their supervisors did not influence students' time to completion. This would suggest that, although supervisors may be crucial to their students' progress, they may not be in a position to influence students to complete their studies more rapidly. The current project also provides direction for future research on master's and doctoral supervision within an ODeL context.

Key Words: Open Distance e-Learning (ODeL); Higher education; Postgraduate education; Time to completion; Student success; Master’s and doctoral supervision; Postgraduate research supervision; Supervision styles; Supervision relationships, South Africa.

List of acronyms

Acronym	Definition		Acronym	Definition
AFGI	Adjusted Goodness of Fit Index		ML	Maximum likelihood
AIC	Akaike Information Criterion		NDP 2030	National Development Plan 2030
ASSAf	Academy of Science of South Africa		NFI	Normed Fit Index
AVE	Average Variance Extracted		NQF	National Qualifications Framework
CFA	Confirmatory Factor Analysis		NRF	National Research Foundation
CFI	Comparative Fit Index		NSFAS	National Student Financial Aid Scheme
CHE	Council on Higher Education		ODeL	Open Distance e-Learning
CR	Composite Reliability		PhD	Doctor of Philosophy
DHET	Department of Higher Education and Training		POPIA	Protection of Personal Information Act
EFA	Exploratory Factor Analysis		QEP	Quality Enhancement Project
EU	European Union		RMSEA	Root Mean Square Error of Approximation
GDP	Gross Domestic Product		SAQA	South African Qualifications Authority
HEDA	Higher Education Data Analyzer		STEM	Science, Technology, Engineering and Mathematics
HEI	Higher Education Institution		SRMR	Standardised Root Mean Square Residual
HEMIS	Higher Education Management Information System		TTC	Time to completion
HEQSF	Higher Education Qualifications Sub-Framework		UK	United Kingdom
ICT	Information and Communication Technology		Unisa	University of South Africa
IDE	Integrated Development Environment		US	United States of America
MI	Modification Index		WTTC	Weighted time to completion
MINRES	Minimal Residuals		-	-

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Chapter 1: Introduction

The following study compares student-supervisor fit and time to completion[1] of master's and doctoral students[2] in a South African Open Distance e-Learning (ODeL) institution. Higher education institutions depend on limited public resources and are expected to produce innovative research (Cloete et al., 2015). This mandate requires that more master's and doctoral students complete their studies in order to increase the research and supervision capacity in higher education (Cloete et al., 2015), as well as ensure that students do not take up limited enrolment space for longer than necessary (Horta et al., 2019; Mouton et al., 2015). Student supervision has been identified in the literature as a critical factor in considering student success and timely completion of master's and doctoral qualifications (Dominguez-Whitehead & Maringe, 2020; Jones, 2013; Van Lill, 2019). However, to date, there has been a dearth of research concerned with how supervision relationships may be measured (Ali et al., 2016; Vilkinas, 2008) and, by extension, what impact supervision relationships have on student time to completion. To address this gap in the literature, a measurement of supervision style preferences for students and their supervisors was developed. This measurement was used to compare students' time to completion with the congruence (fit) between students' and their supervisors' preferences for a particular supervision style.

Identifying the role that supervision relationships play in the completion times of master's and doctoral students in an OdeL context provides valuable insight for higher education institutions (HEIs), and potentially assists policy developers and researchers to gain additional insight into master's and doctoral supervision. Furthermore, higher education institutions would gain an additional perspective to inform monitoring strategies and support initiatives for master's and doctoral students and supervisors. Supervisor training enterprises will be better informed about supervision styles' role in student success. They

[1] The term 'completion' is used throughput this thesis to indicate that students have complied with the requirements of their qualifications and are awarded the degree towards which they were studying (i.e., a master's or doctoral degree).
[2] Both master's students and doctoral candidates will be referred to throughout as 'students' when discussed collectively herein as supervisees.

may thus better equip supervisors to identify barriers and facilitate processes to increase student success and timely completion.

The first chapter of this thesis provides an overview of the research project. The chapter broadly presents the background and rationale, the research context, as well as an overview of the research design. The chapter outline is discussed in the conclusion.

1.1. Background and rationale

A country's development or participation in the knowledge economy is linked to economic growth (Academy of Science of South Africa (ASSAf), 2010; Cloete, 2015; Essop, 2020). New research drives innovation and development, where qualifications and skills (relevant for knowledge creation) are viewed as commodities utilised by countries to participate in the knowledge economy (Cloete et al., 2015; Deuchar, 2008; Laher et al., 2019; Mouton, 2011). As such, the focus is placed on HEIs as societal structures for skills development and knowledge production (Bastalich, 2017; Cloete, 2015; Cloete et al., 2015; Essop, 2020), with increasing attention being placed on the efficiency of the higher education sector and accountability to the labour market (Cloete, 2015; Deuchar, 2008; Lee, 2007; Owler, 2010).

In particular, the focus is typically placed on doctoral education as the highest qualification level achieved through such training, and its role in knowledge creation (Bastalich, 2017; Cloete et al., 2015; Dominguez-Whitehead & Maringe, 2020; Jones, 2013). In turn, master's education acts as the precursor for doctoral studies and has recently received more attention in research. Nonetheless, master's students are increasingly required to participate in knowledge creation through the publication of their research in accredited[3] journals.[4] Thus, similar research production emphasis is placed on master's education, albeit with slightly lower requirements than doctoral qualifications (Essop, 2020; Jones,

[3] In South Africa, public HEIs become eligible for subsidy funding when affiliated authors publish articles in journals that have been approved by the Department of Higher Education and Training (DHET). For institutions to become eligible for these funds, journals must appear on the list of accredited journals published annually by the Department (Ministry of Education, 2003). See section 2.2 Higher education funding.

[4] The University of South Africa formally included this as a requirement for master's students who register for the first time from the 2022 academic year.

2013; Unisa, 2021). Although there is debate over what doctoral graduates contribute to the knowledge economy (Cloete et al., 2015), the focus here is on developing research skills associated with increased knowledge production (Owler, 2010).

To further develop the research capacity and knowledge production in South Africa and "address the developmental needs of our society and economy" (Department of Higher Education and Training, 2013, p. 34), there is a need to increase the number of master's and doctoral graduates (ASSAf, 2010; Breier & Herman, 2017; Department of Higher Education and Training, 2013; Fourie, 2015; Mouton, 2011). South Africa's doctoral output as a proportion of the country's population is lower than other developing countries, such as Brazil, Cuba, Argentina, and México (Breier & Herman, 2017; Department of Higher Education and Training, 2020b). As a result, the South African National Development Plan 2030 (NDP 2030) set a target of 100 doctoral graduates per million of the South African population by 2030. Initially, this target meant that the South African higher education sector needed to produce at least 5 000 doctoral graduates per year (National Planning Commission, 2012). The initial target has been critiqued as being over-ambitious, for lacking the necessary number of applicants and supervision capacity to realise these targets (Essop, 2020; Herman, 2017). Due to population growth, the estimated target would have to be adjusted closer to 6 800 doctoral graduates per year. Despite growth within the sector, the target would appear to remain out of reach within the latest update of the progress on the NDP 2030 (Department of Higher Education and Training, 2020b; National Planning Commission, 2020).

The need to increase graduation numbers drives the requirements for increased enrolment in master's and doctoral programmes (Department of Higher Education and Training, 2013). However, an alternative argument for increasing the doctoral output of the country is to focus on student success (Fourie, 2016; Mouton, 2011) by reducing qualification attrition and the time to completion (increasing efficiency) (Fourie, 2016; Mouton, 2011). In South Africa, a master's can be completed in a single year, while a doctoral qualification requires a minimum of two years (Council on Higher Education, 2009a, 2013b). While these are the minimum time for completion, the average time to completion for a master's student is closer to two or three years (Council on Higher

Education, 2009a; Zewotir et al., 2015), and just under five years for a doctoral candidate (ASSAf, 2010; Council on Higher Education, 2009a; Mouton, 2007; Van Lill, 2019). The average time to completion for doctoral candidates is comparable to international programmes (Mouton, 2007). Nonetheless, increased focus has been placed on the efficiency of student completion times, given that students are partially subsidised through governmental funding (Connell & Manathunga, 2012; Fourie, 2016; Geven et al., 2018). This translates into student throughput and efficient completion becoming factors tracked for national benchmarks (Watson, 2008), and indicators for funding targets (Bastalich, 2017).

The focus on efficiency is not without critique. In contrast to the efficiency focus, some authors (Agné & Mörkenstam, 2018; Breier & Herman, 2017; Connell & Manathunga, 2012; Mouton, 2011; Mouton et al., 2015; Owler, 2010; Palmer, 2016; Spronken-Smith et al., 2018) argue against a sole emphasis on shorter completion times or the number of graduates produced. Instead, these authors (ibid.) argue for a more substantial focus to be placed on improving the quality of academic research. Concentrating only on shorter completion times may cause students or supervisors to sacrifice the quality of their research to ensure timely completion. Whereas so-called 'slow scholarship', which allows for more freedom to conduct innovative research, is therein placed at risk (Connell & Manathunga, 2012; Khosa et al., 2019; Palmer, 2016; Spronken-Smith et al., 2018). By taking on more complex and innovative research, doctoral studies would add value to the country's participation in the knowledge economy (Breier & Herman, 2017). Thus, care must be taken not to trivialise the knowledge creation for which the higher education sector is valued in favour of efficiency (Connell & Manathunga, 2012; Khosa et al., 2019; Owler, 2010). However, one can also argue that there must be progress in order to justify the resources allocated toward higher education research. It is, therefore, necessary to establish a balance between the quality of the research conducted, and a realistic perspective of how this can be accomplished efficiently.

Various factors have been investigated and are found to influence the progress and experiences of doctoral students (Jones, 2013; Sverdlik et al., 2018), who undertake what has been described as a complex and lonely academic journey (Jones, 2013; Owler, 2010; Sowell et al., 2015; Sverdlik et al., 2018). For this reason, students completing master's or doctoral qualifications require guidance and support, which typically falls within their supervisors' ambit (Sambrook et al., 2008). To supervise a master's or doctoral qualification, supervisors need to have at least obtained a qualification at the same level. Thus, the number of students who can enrol for master's and doctoral qualifications would depend on the number of available supervisors to support their research (Breier & Herman, 2017). However, despite incentives for institutions to increase student enrolment, South Africa seems to lack the supervision capacity to meet the NDP 2030 goal for student output (ASSAf, 2010; Cloete et al., 2015; Essop, 2020). Those available and qualified to support doctoral students in South Africa appear to be responsible for an increasing number of students (Council on Higher Education, 2009a; Fourie, 2016; Mouton et al., 2015). This is due to the retirement of ageing academics on the one hand (ASSAf, 2010; Breier & Herman, 2017; Council on Higher Education, 2009a; Department of Higher Education and Training, 2015), as well as to the rapid growth of doctoral student enrolments on the other (Department of Higher Education and Training, 2015).

Supervisors are typically responsible for around seven master's and doctoral students at any given time. In contrast, supervisors in the social sciences are typically expected to supervise around 12 students at once (Council on Higher Education, 2009a). More recent findings suggest that supervisors in South Africa supervise around four doctoral candidates and presumably more master's students simultaneously (Mouton et al., 2015). In addition, Mouton et al. (2015) found that 20% of supervisors were responsible for more than six doctoral candidates at any given time. The supervision load is thus quite uneven.

Master's and doctoral education, and specifically supervision, has received significant attention abroad (Hasgall et al., 2019; Sverdlik et al., 2018) and in South Africa (ASSAf, 2010; Fourie, 2016; Manyike, 2017; Mouton et al., 2015; Van Lill, 2019) for the past several decades (Jones, 2013). Besides the increase in student numbers, academic staff are faced with additional obstacles (Mouton et al., 2015). In particular, the high bureaucratic demands for accountability surrounding supervision place a further administrative burden on supervisors (Hasgall et al., 2019; Mouton et al., 2015) or students' seemingly under-preparedness for doctoral education (Mouton et al., 2015). These additional demands do not decrease supervisors' other responsibilities relating to their research output, administration, and teaching activities, including supervision of other students (Cornelius & Nicol, 2016).

Regardless of the obstacles experienced by supervisors, they are often held accountable for students' unsatisfactory performances or lack of success (Bastalich, 2017; Owler, 2010), where student success indicators have become a determinant of academic promotion on the part of supervisors (Grossman & Crowther, 2015). Students who do not perform according to institutional standards would thus affect the career trajectory of their early career supervisors. This may result in supervisors taking more active and leading roles in the research conducted by their students (Deuchar, 2008), possibly to the detriment of the research autonomy and innovation that is the hallmark of postgraduate student training, and the broader academic project (Deuchar, 2008; Owler, 2010).

It is thus essential to focus on the student-supervisor (supervision) relationship as a factor that influences student progress and success (ASSAf, 2010; Ali et al., 2016; Breier & Herman, 2017; Jones, 2013; Mouton et al., 2015; Sverdlik et al., 2018). Various authors have recognised supervision relationships as a crucial aspect of master's and doctoral education (Abdullah & Evans, 2012; Deuchar, 2008; Jones, 2013; Roach et al., 2019). According to Ali et al. (2016), the relationship between supervisors and supervisees determines the quality of received supervision. According to Bastalich (2017), high-quality supervision relationships would improve the quality of scholarship. Supervision relationships have been reported as one of the most influential factors affecting students' educational experience, where previous research has illustrated the importance of these relationships from students' perspectives (ASSAf, 2010; Sampson et al., 2016). Poor supervision relationships may form a barrier to qualification completion (ASSAf, 2010; Van de Schoot et al., 2013; Van Lill, 2019). Thus, students and supervisors would experience difficulties if their needs and expectations were misaligned (Al-Muallem et al., 2016).

Within this thesis, the concept of 'fit' or 'congruence'[5] in supervision relationships represents the compatibility of students and their supervisors. Students and supervisors could have different levels of compatibility in their interactions, which may relate to the topic they are studying, their level of comfort with a particular methodology, or their interaction styles and supervision preferences (Ives & Rowley, 2005). This thesis focuses on the interpersonal compatibility between students and their supervisors, as represented by their supervision style preferences. This aspect of the supervision relationship seems particularly important, given that Ives and Rowley (2005) found that students and supervisors were willing to sacrifice methodological or topic-related fit for compatible interpersonal relationships. Supervision relationships have also been linked to students' timely completion, albeit based on self-report data, or without providing empirical evidence (Jones, 2013; Roach et al., 2019; Sinclair, 2004). Thus, indicating the need for further research on this subject (Sverdlik et al., 2018; Wright et al., 2007).

Empirical research that focuses on supervision and supervision relationships tends to be qualitative, providing overviews of the experiences relating to supervision practices (Agné & Mörkenstam, 2018; De Kleijn et al., 2012; Ives & Rowley, 2005; Mouton et al., 2015; Olmos-López & Sunderland, 2017; Pifer & Baker, 2016; Sverdlik et al., 2018). Such studies typically provide considerable depth in examining supervision practices and relationships; however, they rarely provide an opportunity to measure the effectiveness of supervision (Agné & Mörkenstam, 2018; Sverdlik et al., 2018). Research on student supervision also tends to involve either students (Wichmann-Hansen & Herrmann, 2017) or supervisors (Gray & Crosta, 2018), where there is a need to include both in investigations of supervisory relationships (Åkerlind & McAlpine, 2017). Thus, despite numerous studies that focus on dissertation or thesis completion, there is a dearth of knowledge regarding supervision relationships (Marshall et al., 2017; Pyhältö et al., 2015), how students classify their ideal supervision relationships (De Kleijn et al., 2014), and research on student supervision in the African context (Rugut, 2017). There is a further need for the development of robust instruments relating to supervision and student supervisors relationships (Ali et al., 2016; Vilkinas, 2008), which may be used to provide

[5] The terms fit and congruence are used interchangeably in this thesis to represent this concept.

insight into master's and doctoral education, students' time to completion, or as an initiative to monitor students' progress or needs (Sverdlik et al., 2018; Vilkinas, 2008). This study thus aims to address the abovementioned concerns by providing insight into supervisory relationships and their role in the time-to-completion of students. The study develops a research instrument and tests the validity of a popular theoretical framework on student supervision within an Open Distance e-Learning (ODeL) context in South Africa. In addition, the results of this thesis may provide HEIs with the necessary information to improve the experiences of both supervisors and students (Ali et al., 2016).

1.1.1. Research context

The research project was conducted at the University of South Africa (Unisa), which is the largest ODeL institution on the African continent, as measured by student enrolment (Universities South Africa, 2021). Unisa is also one of the top ten higher education institutions in South Africa in terms of the number of annual master's and doctoral graduates it produces (Council on Higher Education, 2009a; IDSC, 2021a). Nationally, Unisa accounted for 9.2% of the combined master's and doctoral enrolments at South African public universities in 2017 and 7.6% of the combined master's and doctoral graduates during the same year (Essop, 2020). Disaggregated to qualification level during the same period, Unisa accounted for 10.1% of doctoral enrolments and 9.5% of doctoral graduates (Essop, 2020). In 2019, Unisa was the seventh top producer of master's and doctoral graduates (IDSC, 2021a),[6] the seventh largest for master's, and the fourth largest for doctoral graduates, respectively (IDSC, 2021a). Given the size and ODeL nature of the institution, Unisa provides a unique context for research relating to master's and doctoral education and supervision. The size of Unisa places the institution in a position to significantly influence the production of more master's and doctoral graduates, and affect the research production to address the needs presented in the NDP 2030 (National Planning Commission, 2012).

[6] HEMIS data for all public South African universities are available through the PowerHEDA website developed and hosted by IDSC.

Within this research context, the student success framework, informing the student support initiatives of Unisa, also becomes a critical consideration. Unisa views retention and student success as based on the socio-critical model described by Subotzky and Prinsloo (2011), within which the authors define the student and institution as autonomous, or “situated”, agents with specific backgrounds and contexts (Subotzky & Prinsloo, 2011, p. 184). Success is achieved through the “mutually influential activities, behaviours, attitudes, and responsibilities of students and the institution” (Subotzky & Prinsloo, 2011, p. 184). Both agents are relatively free within their context to grow and develop throughout the students’ academic journey (Subotzky & Prinsloo, 2011). There are various contact points during the journey to assist and monitor students, and support systems are required at various stages to promote student retention and throughput. The ability of students to navigate the student-walk (student journey) or for the institution to support their journey depends on both parties learning more about the other. This knowledge needs to translate into relevant interventions at each stage of the student-walk. Individualised support actioned in this way is argued to create closer alignment (fit) between the institution and students, which is viewed as a precondition to achieving sustainable success (Subotzky & Prinsloo, 2011).

Due to the ODeL nature of the institution, Unisa students are typically not located on or near the university campus. They might conduct their studies outside the geographical boundaries of South Africa (Manyike, 2017). Although this might not be uncommon for master’s and doctoral training, even within institutions with traditional face-to-face teaching modes, the distance mode implies an added aspect to consider for both master’s and doctoral supervision. For instance, while the research journeys of students are described as lonely, this appears to be exacerbated within the distance education model (Andrew, 2012; Nasiri & Mafakheri, 2015).

In distance education, the supervisor would often be considered the primary point of contact for students’ educational journeys instead of the departments or administrative divisions (Cornelius & Nicol, 2016; Gray & Crosta, 2018; Nasiri & Mafakheri, 2015). Geographic separation also makes it more difficult for students and supervisors to get to know one another, making it challenging for their supervision relationships to move beyond formal interaction (Cornelius & Nicol, 2016; Nasiri & Mafakheri, 2015). Nonetheless, not a great deal of extant research specifically considers research supervision within an ODeL context (which may be facilitated through online platforms) (Gray & Crosta, 2018; Kumar & Johnson, 2019; Maor & Currie, 2017), while student supervision within an online learning context has arguably become more critical due to the COVID-19 pandemic.

Overall, the size and ODeL nature of Unisa provides a unique context for a study on master's and doctoral supervision. The size of Unisa positions the institution to address the needs presented in the NDP 2030 (National Planning Commission, 2012). The fact that Unisa is a dedicated ODeL institution means that supervision relationships may have become a stronger focus in master's and doctoral education. Whereas, the student success framework adopted at Unisa also acknowledges the different possible avenues for success and the importance of fit between the students and the institution, for students to achieve successful outcomes (Subotzky & Prinsloo, 2011). The following section introduces the purpose of the study and outlines the research questions answered in this thesis.

1.1.2. Purpose

The HEI sector has increasingly become concerned with students' throughput and time to completion, where the focus is placed on the role of supervisors in driving completion targets. Although the efficiency argument has been critiqued (Agné & Mörkenstam, 2018; Breier & Herman, 2017; Connell & Manathunga, 2012; Mouton, 2011; Mouton et al., 2015; Owler, 2010; Palmer, 2016; Spronken-Smith et al., 2018), determining the role of supervisors within the educational journeys of master's and doctoral students may provide crucial information regarding the supervisors' pedagogical foundations.

This study serves to measure the relationship between student-supervisor fit and the time to completion of students in master's and doctoral education. It was necessary to develop a measurement for master's and doctoral supervision fit, which, in this study, was based on the supervision styles conceptualised by Gatfield (2005). Thereafter, the resulting data was used to correlate supervision preference fit with the time to completion of master's and doctoral students. The assumption that formed the basis for this comparison is that closer supervision fit would lead to a shorter time to completion. The study attempts to answer the following research questions:

- RQ 1: Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?
- RQ 2: Is there a difference between the supervision style preferences of master’s and doctoral students?
    - RQ 2.1: Is there a relationship between the supervision style preferences of master’s and doctoral students and their time to completion?
- RQ 3: Which factors influence the supervision style preferences of master’s and doctoral supervisors?
- RQ 4: Is there a relationship between the congruence of supervision relationships and the time to completion of master’s and doctoral students?

1.2. Research design

This study is situated in a positivist paradigm (De Vos et al., 2011), where the assumption is made that supervision relationships are measurable, and may affect student progress or success. Within this worldview, the study could be defined as exploratory research, given that a research instrument was developed due to the dearth of quantitative research focusing on supervisory relationships. The research design was correlational, focusing on relationships between variables (De Vos et al., 2011; Field et al., 2012), in particular, between the time to completion of students and their supervision relationship fit with their supervisors.

As this is a correlational research design, a cross-sectional online survey was deemed suitable to provide the most appropriate method of collecting data. Online cross-sectional surveys ensured minimal interference with supervision relationships and students’ research progress. The study used self-report measurements to collect data that could be used to create an index of supervision preferences and could be used to infer information about the supervision relationship fit.

1.2.1. Population

This study was conducted among two research populations, namely: Unisa students and supervisors. The student population for this study included master's and doctoral students who were registered for the 2019 academic year at Unisa, or recent graduates who had completed their master's or doctoral qualifications (those who graduated in 2017, 2018, and 2019). According to the publicly available peer data, there were in total 7 501 students enrolled for qualifications at master's (5 020) and doctoral (2 481) levels at Unisa during 2019 (IDSC, 2021d). During the years of interest (2017-2019), there was a total of 3 626 graduates at the master's (2 688) and doctoral (938) levels (IDSC, 2021a). Thus, the total student population for the research can be estimated to be 11 127, and the Unisa ICT department sent 11 762 emails to invite participation (P. Ngoepe, personal communication, October 17, 2019).

The second population consisted of master's and doctoral supervisors. Supervision statuses needed to be estimated based on available data because these are not flagged or publicly reported. Supervisors are typically academic or teaching staff. However, support staff can take on supervisory roles as well. The University additionally employs external supervisors under certain conditions, although typically, in a supporting co-supervision capacity. Since supervisors need to be qualified at the level at which they supervise, all academic and professional support staff (both permanently and temporarily employed) who hold master's or doctoral qualifications were counted, which estimated a total of 1 409 staff during 2019 (IDSC, 2021c). The University ICT department sent out a total of 1 676 email invitations to potential supervisors (P. Ngoepe, personal communication, October 17, 2019).

1.2.2. Sample

Within this project, a census approach was used since there were no logistical reasons to reduce the number of potential respondents, similar to the approach found in Ali et al. (2016). Therefore, the research depended on the number of voluntary responses from students and supervisors who formed the study sample for this project.

To test the generalisability of the data, conventional social science sampling assumptions are used, where the confidence level was 95%, and the acceptable margin of error was assumed to be 5% (Field et al., 2012; Raosoft Inc., 2004). Based on these assumptions, the ideal sample sizes were estimated to be 373 for students and 313 for supervisors for generalisation (Raosoft Inc., 2004).

After data cleaning, 1 323 unique student responses were recorded (included in the data validation of the survey data), of which 1 183 responses could be linked to institutional records, representing a 10.05% response rate of the distributed emails. Similarly, 180 unique supervisor responses were recorded, of which 169 could be linked to institutional information, representing a 10.08% response rate. The student sample is more than large enough for inferences about the master's and doctoral student population. Although for the supervisor sample, the results would not be generalisable for the supervisor population since the margin of error is 6.9%, which is slightly higher than the typical assumption of 5%. Nonetheless, 137 relationships could be identified linking a student's record with their supervisor. Within the linked student-supervisor dataset, 69 student respondents had completed their respective qualifications.

1.2.3. Research instrument

A questionnaire was designed to measure supervision preferences based on the theory of supervision proposed by Gatfield (2005). It was necessary to design a questionnaire, as none of the available instruments was consistent with the purpose of this study. In line with best practices, the development of the questions relied on available literature and the theoretical framework (De Vos et al., 2011; Hair et al., 2014; Terre Blanche et al., 2006). The questions were intended to measure structural and support elements outlined in an article by Gatfield (2005). Additional contextual factors were noted in the development of the measurement for it to remain relevant to supervision at Unisa. The wording of the questions was adapted so as to create a measurement for students and another for supervisors, each consisting of 51 Likert-type questions that were developed on a seven-point scale. The conceptualised Structure construct consisted of 31 questions, whereas the Support construct contained 20 questions. Both positive and negatively phrased questions were used in this study.

1.2.4. Process and data collection

The questionnaires were distributed through an online survey platform. This data collection method was considered the most appropriate, as the population was geographically dispersed, but still accessible through electronic communication channels. Online surveys allow respondents to complete the questions in their own time, and automate the data-capturing process so as to avoid any capturing mistakes (De Vos et al., 2011).

Identifiers were required, as student and supervisor data needed to be linked to investigate supervision fit. For these purposes, student respondents were asked to provide their student numbers, and supervisors were asked for their staff numbers (while external supervisors were asked to share their email addresses). After data was collected from respondents, the Unisa ICT Department was asked to provide the necessary data to link the information of students and staff, in addition to including relevant variables for this study (such as the start and completion dates needed to calculate the time to completion). The data was anonymised once the student and staff records were linked, in order to protect the privacy of respondents.

The time to completion was determined by the number of months (Agné & Mörkenstam, 2018; Watson, 2008) between the students' first registration date for their qualification and the results date for their dissertation or thesis. The time to completion for each student was reduced by the minimum time of their qualifications in order to facilitate comparisons between master's and doctoral qualifications (Palmer, 2016). As such, master's students' time to completion (measured in months) was reduced by 12 months, and doctoral students' times were reduced by 24 months (the minimum times for completion). The new weighted time to completion measures thus reflects the number of months students took longer than the minimum qualification time, whereas those who completed within the minimum time would be recorded as zero (0).

1.2.5. Data analysis

The data were analysed through descriptive statistics, factor analysis, and inferential statistics. Descriptive techniques, such as frequencies and measures of central tendency, were used to summarise and inspect the response distributions of the variables. This analysis assisted in the investigation of data assumptions, and described the study sample for contextualisation of the results.

The responses to the student questionnaire were investigated with a combination of factor analysis techniques in order to examine the instrument's validity. Confirmatory factor analysis (CFA) was first used to test whether the intended question structure was reflected in the collected data (Hair et al., 2014; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013). This was followed by an exploratory factor analysis (EFA), which investigated possible alternative factor structures in the data (Hair et al., 2014; Orcan, 2018; Yong & Pearce, 2013). For the EFA, the data were randomly split into a training (n = 595) and test (n = 728) datasets. The training data was used to identify a possible factor structure through an EFA, whereas each identified model was checked via CFA using the test dataset. For this aspect of the analysis, only the student data provided sufficient responses to be considered. Using student data was also consistent with theoretical considerations, given that students' experiences are assumed to affect their academic performance. This approach shared similarities with Al-Muallem et al. (2016). The instrument's reliability was explored with composite reliability within the CFA measures and Cronbach's alpha.

After exploring the validity and reliability, an appropriate model was selected, and indices were created to use throughout the data analysis. Relationships and differences were investigated using non-parametric inferential statistics. The inferential analysis primarily utilised non-parametric analytical techniques, in some instances due to the violations of parametric assumptions, and in others due to sample size. The non-parametric techniques used for the comparisons included a Wilcoxon rank-sum test (for comparisons between two groups), the Kruskal-Wallis test (for comparisons that contain more than two groups), and a Spearman correlation, which was used to test for relationships between two continuous variables. The effect sizes used to measure the strength of differences or relationships included the 'eta^2' (η^2) and 'r'.

1.2.6. Ethics

Ethical clearance for this project was obtained from the Ethics committees of the Department of Psychology, the Unisa College of Human Sciences Research Ethics Committee, as well as the Research Permission Sub-Committee (RPSC) of the Senate Research, Innovation, Postgraduate Degrees and Commercialisation Committee (SRIPCC) (see Appendix D for clearance certificates), in line with the requirements from the Protection of Personal Information Act (POPIA). Respondents could voluntarily access the online survey through a generic link, which directed each respondent to an information page, and could withdraw at any point during the study. Consent was explicitly requested, whereafter respondents were asked to provide identifiable information to connect students with their supervisors, as previously described (see section 1.2.4). Once the data was combined, the identifiable information was removed in order to protect the respondents' identities, where the data was still treated as confidential. Additionally, only aggregated, analysed data is presented.

1.3. Chapter outline

The thesis is divided into seven chapters. This first chapter provides a brief introduction and overview of the research topic and purpose. The research design and document structure are outlined to contextualise the study. The remaining chapters are divided into the following topics for discussion: literature review; theoretical framework; overview of the research method; the validity of the research instrument; overall project results; and the discussion and conclusion of the study. Each chapter is briefly introduced below.

1.3.1. Chapter 2: Literature

The literature review chapter provides an overview and comparison of master's and doctoral education within the South African higher education context. Different perspectives and indicators for student success are introduced and compared, and the factors that may influence student success and time to completion are identified in previous research. The chapter concludes with a discussion of different models of training and supervision that apply to master's and doctoral education.

1.3.2. Chapter 3: Supervisory relationships

The third chapter provides an overview of theoretical approaches for examining master's and doctoral supervision. This chapter links two theoretical approaches to facilitate the investigation of supervision relationships in master's and doctoral education: 1) fit theory provides the theoretical basis to assume that congruence or misalignment in the student-supervisor relationship would impact or impede the success of master's and doctoral students; and 2) the supervision framework proposed by Gatfield (2005) was adopted, which posits that supervisory relationships can be described through the amount of structure or support that students and supervisors experience. The combination of the two theoretical frameworks provides the foundation for the assumption that congruent experiences or perceptions of supervision relationships between students and their supervisors would enhance student success (within this study, measured as students' time to completion).

1.3.3. Chapter 4: Method

The fourth chapter discusses the research method applied to answer the research questions. The study is designed within the positivist paradigm, which assumes that the variables under investigation, specifically supervision relationships, can be both defined and measured. The most appropriate design for the study is described as exploratory and correlational research. The chapter includes a brief outline of the student and supervisor populations and sample before, providing a detailed overview of the research instrument's development and design. An in-depth discussion of the process to determine the validity and reliability of the research instrument is explored, which focused on how confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) are utilised in the investigation of the research instrument. Before outlining how the data is analysed to respond to the research questions. The chapter concludes with a discussion of ethical permissions and considerations.

1.3.4. Chapter 5: Instrument validation

Chapter Five provides a detailed overview of the validity and reliability of the research instrument as a response to the first research question within this study (RQ 1). The chapter commences with a descriptive account of the research instrument variables, and an investigation of the data assumptions. The theoretical basis of the research instrument is tested with a CFA, after which alternative factor structures are investigated through an EFA and confirmed through CFA. The chapter presents the results for all the investigated, factor structures and provides a comparative overview of each. Although the initial predicted CFA models and the subsequent exploratory EFA/CFA models are similar conceptually, some minor differences are recognised and discussed.

1.3.5. Chapter 6: Results

The research results, which respond to the remaining three research questions, are presented in Chapter Six. The chapter is divided into three sections, each addressing one of the research questions. The first section provides an overview of the student data, describing the sample and the relevant measures for this study. The primary purpose of this section is to consider possible differences in supervision preferences between master’s and doctoral students (RQ 2), and whether there is a relationship between students’ preferences and their time to completion (RQ 2.1). The second section of this chapter concerns the supervisor data, which provides a descriptive overview of the supervisors’ preferences and relevant variables that were measured. This section aims to investigate which factors would influence the supervision style preferences of supervisors (RQ 3). The student and staff data are linked (where possible) and combined to respond to the final research question in the chapter’s third section. The chapter thus concludes by investigating a relationship between the congruence of supervision relationships, and the time to completion of master’s and doctoral students (RQ 4).

1.3.6. Chapter 7: Discussion and conclusion

Finally, Chapter Seven concludes the thesis through a discussion and contextualisation of the results, as presented in chapters Five and Six. The chapter is divided into four sections in order to address each of the research questions, thereby providing an overview of the validation of the research instrument (RQ 1), a discussion of the student data (RQ 2 and RQ 2.1) and the supervisor data (RQ 3), as well as the discussion of the relationship between supervision fit and time to completion (RQ 4). The chapter concludes by describing the limitations experienced within this research, and possible recommendations for future studies.

Chapter 2: Literature

This chapter provides a contextual basis for the study, where an overview of master's and doctoral education is provided, specific to the South African educational context. Policy directives and qualification criteria are considered in order to compare and describe master's and doctoral education. Following the discussion on master's and doctoral qualifications, an outline of the different measures of student success used within the South African and international educational contexts is presented. In addition, the measures of success and success matrices are compared, using previous research in order to provide context for the current study regarding throughput and time to completion of qualifications. Furthermore, previous studies examining factors influencing student success, particularly master's and doctoral education, are presented. The influence of master's and doctoral supervision is outlined, and different training and supervision models are discussed in order to conclude the chapter.

2.1. Master's and doctoral qualification structure

Three organisations within the South African higher education system are critical to understanding the structure of higher education qualifications, namely: 1) the Department of Higher Education and Training (DHET), which has the ultimate responsibility for the higher education sector and provides leadership and guidance; 2) the Council on Higher Education (CHE), which is an independent organisation that acts as an accrediting body for all qualification requirements in order to quality assure qualifications within South Africa. This task was assisted by developing and managing the Higher Education Qualifications Sub-Framework (HEQSF); and 3) The South African Qualifications Authority (SAQA), which was established to develop policies and criteria to register qualifications under the National Qualifications Framework (NQF) (Council on Higher Education, 2013b; Post-School Education and Training Monitor: Macro-Indicator Trends, 2019). For higher education institutions to be able to enrol students into an accredited qualification programme, such a programme would first need to be positioned at an appropriate NQF level, and have been reviewed and approved by the organisations listed above.

The NQF divides the exit criteria for South African qualifications into ten levels. Each level is further subdivided into ten learning outcomes or competencies that govern the knowledge or skills required for attaining a particular level (SAQA, 2012). These competencies are:

A. *scope of knowledge*
B. knowledge literacy
C. method and procedures
D. problem solving
E. ethics and professional practice
F. accessing, processing and managing information
G. producing and communicating of information
H. context and systems
I. management of learning
J. *accountability*

(SAQA, 2012, p. 3)

NQF levels one to four fall within the ambit of the basic education system, whereas the higher education system includes these as basic requirements, but focuses on level five (Higher Certificates) to level ten (PhD and doctoral qualifications) (Council on Higher Education, 2013b). This study focuses on NQF level nine (master's) and NQF level ten (doctoral) qualifications (Figure 1). The study considers a brief overview of master's and doctoral qualifications in order to highlight similarities that would make these qualifications comparable, showing the differences that make each level distinct. See the SAQA level descriptors for the full description of each NQF level of both qualifications (SAQA, 2012, pp. 11–13).

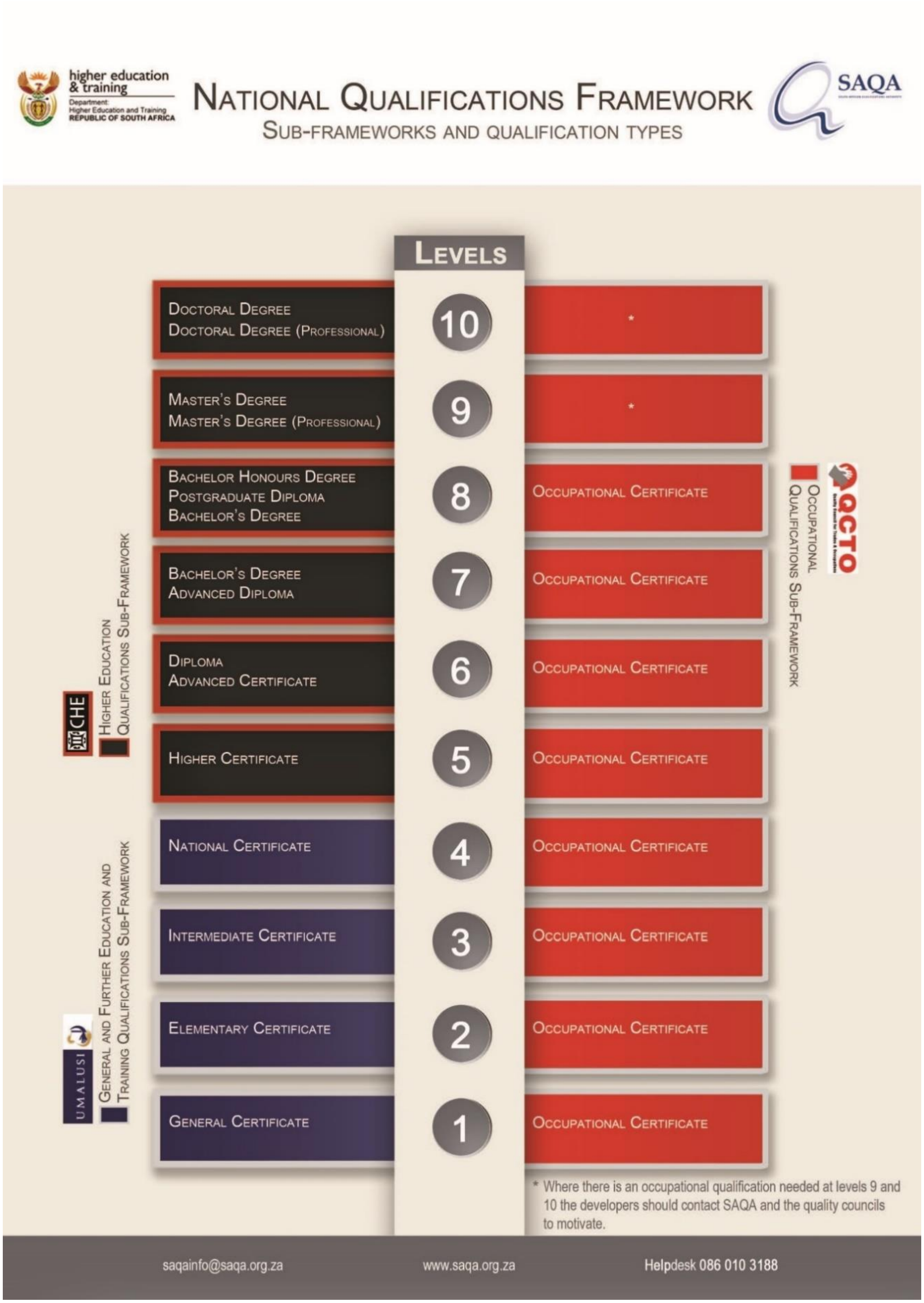

Figure 1: National Qualifications Framework Levels

Source: (SAQA, n.d.)

Similarities between NQF levels nine and ten include research intensiveness and require students to engage with current specialised knowledge and research practices (SAQA, 2012). According to the NQF, students at both degree levels (master’s and doctoral) need to be able to engage with knowledge production processes and use appropriate research design during their engagement. Students need to display the ability to recognise problems within their field of study, and make use of their specialised knowledge to address such problems, while showing that they can be autonomous in ethical decisions made around their field of research (SAQA, 2012). Students must display their ability to engage with current knowledge production, and the technical skills of processing and synthesising information, while also demonstrating their ability to communicate their arguments to their target audiences (SAQA, 2012).

The NQF suggests that students (both master’s and doctoral) must demonstrate an advanced understanding of complex systems and interact appropriately in order to affect changes. Students also need to display the ability to manage their learning, and become increasingly independent, while remaining accountable for their actions throughout the process (SAQA, 2012). The two-level descriptors use different terminology, although the learning outcomes overlap in order to allow those with a master’s (NQF level nine) to pursue doctoral education (NQF level ten). As a result, substantial similarities are apparent.

The main difference in this instance is that, where NQF level nine students need to display their ability to conduct research, NQF level ten students need to display the ability to add to the academic project and knowledge production (Owler, 2010; SAQA, 2012). The doctoral (NQF level ten) focuses on “new knowledge or practice”, and descriptions concentrate on “novel” and “emerging”, which add the requirement of producing knowledge through their learning (SAQA, 2012). A perspective shared with doctoral programmes abroad, such as in Australia (Jiranek, 2010) and the European Union (EU) (Hasgall et al., 2019). Notably, the requirement of producing new knowledge should not imply that such studies are without error (Åkerlind & McAlpine, 2017; Connell, 1985; Connell & Manathunga, 2012; Kiley, 2009), but rather, are an indication that as a researcher, someone has achieved a necessary level of competence (Council on Higher

Education, 2013b; SAQA, 2012). This difference between master's and doctoral education is also not quite as prominent as it was before, with master's students increasingly being expected to publish their research (Jones, 2013).

To provide more detailed guidance to institutions that host qualifications with NQF exit levels of five or above (including NQF nine and ten), the CHE developed the HEQSF based on the requirements set within the NQF (Council on Higher Education, 2013b). The HEQSF provides detailed instruction around the qualifications structure, including the names and designations required; the length of study (or qualification intensity); and qualification entrance requirements and articulation to other qualification levels. The HEQSF further distinguishes between two types of qualifications (academic or professional qualifications), each at NQF level nine (master's) and ten (doctoral).

The first distinction between master's and doctoral education is the intensity of the qualifications, with a master's education requiring 180 credits to be obtained, translating to 1 800 notional hours of study,[7] which can presumably be done in a single year (Council on Higher Education, 2013b). In contrast, doctoral education requires 360 credits to be obtained, which would take a minimum of two years of study on a full-time basis[8] (Council on Higher Education, 2013b). Besides the similarities already described between the two NQF levels, the similarities between the four conceptualised qualifications (professional and non-professional master's and doctoral qualifications) include a specific focus on conducting research (Council on Higher Education, 2013b). Within the HEQSF, the academic qualification focuses on a single project, which culminates in a thesis or dissertation. However, the allowance is made to submit published articles for consideration for a doctorate.

Like doctoral candidates, master's students must conduct research within a specialised study area (Zewotir et al., 2015). Although the new or novel is not a formal requirement of master's education, the HEQSF provides for the possibility that the dissertation

[7] One credit is equal to ten hours of study.
[8] The HEQSF guideline assume that full-time master's and doctoral students are engaged with their studies for 45 weeks per year, for 40 hours per week, "thus requiring a minimum credit-load of […] 180 credits per academic year for Master's Degrees and Doctorates." (Council on Higher Education, 2013b, p. 10).

component may take the form of “a series of peer-reviewed articles” (Council on Higher Education, 2013b, p. 33). In this instance, more novel results are likely a requirement. Quality assurance mechanisms through the previously discussed HEQSF are in place to ensure that students cannot submit their work before the minimum time of one year – for master’s and two years – for a doctorate, has elapsed (Council on Higher Education, 2013b; Watson, 2008).

The professional qualifications, for both master’s and doctoral studies, include a coursework component meant to increase specialised knowledge within the study field and provide an additional layer of structure to such qualifications (Council on Higher Education, 2013b). Students are typically required to take several modules that provide advanced discipline-specific or professionally focused training, in addition to conducting research as part of the training programme. This research component is typically of limited scope[9], representing a smaller component of the qualification when compared to full research qualifications (Council on Higher Education, 2013b).

Given the strong research focus, and the multitude of similarities between master’s and doctoral qualifications, as well as that master’s and doctoral students seem to have similar perceptions of their supervisors (Lessing & Schulze, 2002), it is arguable that the education process is similar enough to incorporate both in a study on research supervision. This would include academic and professional qualifications, given the research focus. Although differences in the qualification outcomes and structures are recognised, the current study focuses on the supervision relationships formed throughout students’ educational experiences during the research component and thus are considered similar enough to be comparable within the current project (Anderson et al., 2006; Connell, 1985).

The explicit assumption is that master’s and doctoral research supervision are similar, and that supervisors take similar roles in relation to students at both levels of study. There would be some risk in assuming that supervisors treat their doctoral candidates and master’s students the same. However, supervision relationships would conceivably be

[9] Referred to as a master’s of limited scope in this thesis.

similar, despite the higher expectations of supervisors in relation to their doctoral candidates.

The bulk of the research on master's and doctoral education has typically focused on doctoral studies. As a result, cited studies typically refer to doctoral education, particularly the difficulties around preparing students to submit work that would provide a new contribution to their fields of study. In this thesis, research focusing exclusively on doctoral education was considered applicable to master's qualifications, due to the argued similarities, as consistent with the approach taken by Anderson et al. (2006). The following section provides a comparative and international outline of master's and doctoral education, before describing how South African Higher Education funding is implemented.

2.1.1. Comparison with international master's and doctoral education

Master's and doctoral research conducted internationally seems to share a similar focus to that of South Africa. In Europe, similar to the requirements in South Africa, doctoral qualifications act primarily as confirmation that graduates conformed to the required standards and are thus capable of conducting research independently, illustrated through the completion of a thesis or publication of research articles (Cornér et al., 2017; Hasgall et al., 2019). In contrast to the South African context, students enrolled for a doctoral programme, or enrolled for a master's as part of a 'doctoral trajectory', may leave their qualification before qualifying for a doctorate, qualifying in so doing for a master's degree (Sowell et al., 2008; Van de Schoot et al., 2013). As such, streamlining students' academic paths from the start of a master's qualification through to completing a doctorate (Van de Schoot et al., 2013). A similar approach is taken in most cases in the United States of America (US) (Sowell et al., 2015). However, countries such as Finland or Denmark already require doctoral applicants to have a master's degree before entering doctoral programmes (Cornér et al., 2017; Wichmann-Hansen & Herrmann, 2017). In New Zealand, a PhD may follow the completion of either honour's or a master's degree (Spronken-Smith et al., 2018), sharing some similarities with the South African educational system. The ultimate completion of a doctoral qualification has, however, moved away from merely signalling a person's ability to form part of the academic staff, but also indicates the ability to be a research professional (Hasgall et al., 2019). The purpose of doctoral education seems to be shifting away from a pure focus on academic careers to include a professional focus for those who would seek employment outside of the Higher Education sector (ASSAf, 2010; Cloete et al., 2015; Jones, 2013; Pearson & Brew, 2002).

Doctoral education seems to have become more structured abroad, with the majority of institutions in Europe indicating that their programmes included components of suggested coursework material as part of these qualifications (Cornér et al., 2017; Hasgall et al., 2019; Wichmann-Hansen & Herrmann, 2017), although this still seems rare in New Zealand (Spronken-Smith et al., 2018). In European countries, students are treated as employees of their universities, in a more contractual (structured) nature of doctoral education (Agné & Mörkenstam, 2018; Van de Schoot et al., 2013; Wichmann-Hansen & Herrmann, 2017). European higher education institutions typically manage the quality assurance of their qualifications internally, where the inclusion of an external organisation in the review process is optional, rather than required (Hasgall et al., 2019). Students are guided through the process by a senior academic or multiple senior academic staff members, who act as supervisor(s) for their studies (Ali et al., 2016; Halse & Malfroy, 2010; Hasgall et al., 2019; Van de Schoot et al., 2013; Wichmann-Hansen & Herrmann, 2017), which is an aspect similar to that found in the US (Sowell et al., 2015), as well as New Zealand (Spronken-Smith et al., 2018).

Durette et al. (2016) argue that when considering students' educational experiences, doctoral education tends to manifest in a way that is somewhat unique to the individual student. However, the authors (ibid.) found that there is an overlap in the competencies developed through such training. The authors argue that the competencies developed through their doctoral training in France are similar to what they have found in literature outside their context (ibid.). This was interpreted to suggest that there is some homogeneity in the training of doctoral candidates, at least for programmes in western countries (Durette et al., 2016). By extension, the findings of this thesis might also apply to supervision research in other countries.

The following section briefly reviews higher education funding in South Africa. This section highlights the investment made into the sector, particularly for different forms of knowledge creation. In turn, this holds an implicit expectation that there would be a return on investment in the form of skilled graduates contributing to the knowledge economy.

2.2. Higher education funding

Higher education requires a significant financial investment to produce competent graduates (Sowell et al., 2008). Funding systems usually depend on national policies. In South Africa, funding typically includes a combination of public funding (via governmental subsidies), external investments (via donor funding or direct investments), and student tuition fees (typically paid by students or bursaries during registration) (Statistics South Africa, 2020). Nationally, in 2019, 48% of the income in the higher education sector came via governmental grants, 33% was generated through tuition, and 19% was raised in donations (Statistics South Africa, 2020). This highlights how dependent South African institutions of higher learning are on governmental funds and student tuition fees. For the institution under study, namely Unisa, 52% of the income received was from governmental grants, 39% was generated through tuition, and 9% was raised in donations during the same timeframe (Statistics South Africa, 2020).

Governmental funding in South Africa is provided through what is known as block grants that cover operational costs, and earmarked grants that focus on further assistance in specific areas (such as the National Student Financial Aid Scheme (NSFAS), which focuses on undergraduate funding) (Styger et al., 2015).[10] Block grants are further divided into ‘teaching input’; ‘teaching output’; and ‘research output’ grants, which consider the number of students who are either enrolled (teaching input), or the number of students who graduate (teaching output), and the amount of research that is produced (research outputs) (Styger et al., 2015).

This framework allows DHET to monitor institutional progress in achieving policy targets, and is weighted to incentivise the achievement of national goals, primarily in the form of

[10] See Styger et al. (2015) for a comprehensive overview of the current funding model.

outputs (Mouton, 2011). Although master's and doctoral studies are partially funded through the teaching input avenue (weighted by study level and classified according to the field of study), the primary funding income for HEI that enrol NQF nine and ten students is through the research output grants (Department of Higher Education & and Training (DHET), 2018; Styger et al., 2015; Zewotir et al., 2015). Research output grants are calculated per institution, in units. Approved publications (such as journal articles, books, and other scholarly outputs) each count as a single unit point shared among the authors. Research master's degrees each count a single point towards the research contribution, whereas doctoral qualifications count three points, highlighting the importance placed on these qualifications (Department of Higher Education & and Training (DHET), 2018; Styger et al., 2015).

The total grant funding for research output units varies for each academic year. Between 2014 and 2016, each research unit was worth just above R100 000. However, the research unit value decreased slightly from R108 692 to R102 518 during this period (IDSC, 2021b). The research funding increased above R120 000 from 2017, where the funding amount was R127 962 in 2020 (IDSC, 2021b). Thus, institutions would have been paid just under R130 000 for each master's graduate and R390 000 for each doctoral graduate, in addition to funding from relevant teaching input subsidies, tuition fees, or publications that resulted from such studies during 2018.

Nonetheless, the governmental funding for research expenditure has declined from 0.92% of the gross domestic product (GDP) in 2007 (National Planning Commission, 2012), to 0.62% of the GDP in 2019 (National Advisory Council on Innovation, 2022). In comparison, Brazil dedicated 1.16% of their GDP to research expenditures in 2018, and China invested 2.14% of their GDP during the same time (National Advisory Council on Innovation, 2022). In addition, this meant that research funding fell short of the 1.5% of the GDP by 2019 target set in the Medium-Term Strategic Framework (Department of Science and Innovation, n.d.). The result of this has been that grants were allocated less frequently and in lower amounts, which has the strongest impact on institutions with fewer international funding connections or third-stream incomes,[11] and more dependent on governmental subsidies (Essop, 2020).

Similar subsidy systems seem to be evident abroad (Australia and Netherlands as examples), where universities gained a fixed sum for each output, regardless of how long this takes (Jiranek, 2010; Van de Schoot et al., 2013). Mouton et al. (2015, p. 3) indicated that funding doctoral candidates in South Africa were behind that of international institutions: “This underscores one of the huge differences between the South African system and that of other countries. In countries such as the US, Canada, the United Kingdom (UK) and other European countries, there is sufficient funding to support doctoral students to study full time.” For example, in the Netherlands, universities are awarded a significant sum (€90 000) when doctoral candidates complete their studies (Van de Schoot et al., 2013). In addition, students are typically supported financially, citing specifically the practice in Sweden where doctoral candidates are essentially employed, receive salaries while studying, and can build work experience by teaching during this time (Agné & Mörkenstam, 2018; Mouton et al., 2015). Similar practices of employing doctoral candidates are followed in Denmark, through industry funding (Wichmann-Hansen & Herrmann, 2017), and in the Netherlands (Van de Schoot et al., 2013). In the US, students may also receive financial support through their departments and find temporary employment as assistants in research, teaching, or fellowships (Sowell et al., 2015).

Although such funding practices seem to show promise, Wichmann-Hansen and Herrmann (2017) highlight that universities globally needed to increasingly find external funding for projects, due to a decrease in institutional funding since the 1990s. This is based on sources indicating the same trend in several countries (including the US and Sweden, mentioned above) that experience such a reduction in funding (Wichmann-Hansen & Herrmann, 2017). By way of contrast, funding in Europe is not homogeneous, with some countries continuing to invest public funds, whilst others experience a decline

[11] Third-stream income is defined by the CHE as; “all university income derived from sources other than state subsidy or student tuition fees […] and can include donations or endowments; money earned through contract research or entrepreneurial activity; and income from investments” (Council on Higher Education, 2019, p. v).

in funding (Hasgall et al., 2019). South Africa has also seen a decline in public funding (ASSAf, 2010), where institutions must invest more resources to find support in collaboration with industry and so-called third-stream income (ASSAf, 2010). However, directives to find more revenue streams through partnerships seem to typically fall to supervisors (ASSAf, 2010; Wichmann-Hansen & Herrmann, 2017), who become increasingly pressured into providing evidence of performance or success (Wichmann-Hansen & Herrmann, 2017), regardless of their level of experience (Fourie, 2016).

With the number of resources that are dedicated to doctoral education (Geven et al., 2018), as well as the increased effort and competition in gaining the required funding from third-stream sources (ASSAf, 2010), there is more attention placed on the output of doctoral graduates (Geven et al., 2018). Students not only need to finish their qualifications to add to the knowledge economy but are also required to do it quickly enough not to take up more resources than are necessary to progress (Geven et al., 2018). The training of doctoral graduates is, in turn, intended to increase participation in and the growth of the economy, not only the conferment of a certificate from institutions of higher learning (Department of Higher Education and Training, 2013).

It is difficult to judge the success of such initiatives. These trends require that a clear definition of success for master's and doctoral education be determined as a measurement outcome. It would only be possible to judge the outcomes of master's and doctoral education if there is a measurable definition of what success entails.

2.3. Views of student success

Within the higher education sector, success refers, broadly, to students who have complied with their qualification requirements and thus have obtained their degree, marked with the graduation processes. The South African Council on Higher Education (2009b), nonetheless, acknowledged that there are multiple possible conceptualisations about what success may look like, listing: "self-development and improved employment prospects of individuals, meeting national and regional labour needs and contributing to the economy and society" (2009b, p. 29). The National Research Foundation (NRF) more recently focused on research funding by electing the impact[12] of funded research as one of its four critical success factors, along with transformation[13], excellence, and sustainability (NRF Strategic Plan 2020 - 2025, n.d.). The focus is placed on impact here since it relates the strongest to individual research rather than sector-wide development. In comparison, another perspective focuses on student learning rather than on attaining a qualification (Owler, 2010).

Unisa's socio-critical model also focuses on defining success in relation to students. The model cites course success such as graduation or timely completion, as typical defining characteristics of student success. However, the model further considers students' contribution to society, such as engagement in the employment market, as well as student satisfaction as possible measures of success. The authors furthermore raise the possibility of attaining success without graduation, where students may transfer to another institution, or through self-development (Subotzky & Prinsloo, 2011).

The above-mentioned individualised conceptualisation of success as discussed by Subotzky and Prinsloo (2011) would be difficult to measure, since the operationalisation and data required would not be readily available (Council on Higher Education, 2009b). Due to the need to clarify what success within the South African higher education sector might mean, the Quality Enhancement Project (QEP) was developed (Council on Higher Education, 2013a). The main focus of the QEP was to enhance student success, which referred to "increasing the number of graduates with attributes that are personally, professionally and socially valuable" (Council on Higher Education, 2013a, p. 26).

In this approach, student success is based on a cost-benefit perspective of higher education qualifications. The benefits of increased degree attainment can be linked to

[12] Impact within this context refers to: "In brief, it is about the impact of research outside of academia and about the direct or indirect causal relationship between knowledge production and improvement in the quality of people's lives" (NRF Strategic Plan 2020 - 2025, n.d., p. 8).

[13] Transformation in higher education is also important to note. The term refers to "… a process of transition from the legacies of the apartheid past, with its ideologies and discriminatory practices, into a new democratic era with new or modified practices, institutions, values and beliefs that have societal legitimacy" (NRF Strategic Plan 2020 - 2025, n.d., p. 8). Although this is not a focus in this thesis, transformation does have an impact on higher education training, and supervision. Where efforts to transform the higher education sector typically focus on the number and proportion of enrolments and graduates from different racial groups and gender identities.

increased expertise available to industry and the development of the knowledge economy (Mouton, 2011), in addition to potentially increasing the employability and earning potential of graduates. There is also a reputational benefit for institutions to increase master's and doctoral graduates, and the status afforded to the growth of research publications (Gardner, 2009; Hasgall et al., 2019; Schulze, 2011). As previously presented, there is a significant investment in higher education training. Therefore, a significant loss is also attributed to student attrition (Golde, 2005). The cost of attrition or failure would include a loss of personal and institutional investment (monetary as well as time commitments) (Golde, 2005; Kelley & Salisbury-Glennon, 2016). Although individuals who drop out may nevertheless be able to utilise their skills (Subotzky & Prinsloo, 2011), they likely do not leave the institution with the added credibility that accompanies completed qualifications (Mouton, 2011).

Training individuals who take longer to complete their qualifications increases costs (Styger et al., 2015), where students tend to eventually complete if they remain registered for longer, particularly after the prescribed qualification minimum time (Watson, 2008), or after the first two years, in the case of a doctoral degree (Mouton, 2011). However, this extended time in the system places the higher education system under strain to support students for longer than planned (Horta et al., 2019; Mouton et al., 2015).

On the other hand, an argument can be made against such a strong focus on efficiency, as certain forms of research or knowledge generation cannot be rushed (Spronken-Smith et al., 2018). Concerns are raised that students or supervisors may decide on more straightforward research projects, with shorter completion times (Connell & Manathunga, 2012; Palmer, 2016; Spronken-Smith et al., 2018), or be tempted to submit prematurely, therein sacrificing quality for speed (Carter & Kumar, 2017; Spronken-Smith et al., 2018). More structured courses and increased directive requirements threaten both autonomy and knowledge creation (Connell & Manathunga, 2012; Frick et al., 2017), as well as the quality of the educational process (Connell & Manathunga, 2012; Khosa et al., 2019; Palmer, 2016; Spronken-Smith et al., 2018), which is so highly valued. The long-term effects of approaches that prioritise quantity over quality would ultimately devalue the knowledge created, and may result in under-skilled graduates and supervisors (Connell

& Manathunga, 2012; Frick et al., 2017; Khosa et al., 2019; Waghid, 2015). As such, conceptualisations of success should be carefully considered in the policies and research around master's and doctoral education (Frick et al., 2017).

Several measures are utilised to determine the success of training programmes. These measures are arguably flawed. However, as Palmer (2016) notes, even the critics of these measures would be hard-pressed to present viable alternative measurements, however, cautioning to guard against over-evaluation by tracking too many performance metrics. As such, completion statistics seem to have become the dominant indicator for the success of interventions and supervision, particularly for funders (Palmer, 2016). Completion statistics may consider the proportion of students who complete their qualifications, complete within the minimum time, or average the number of years that students take to complete their studies (Council on Higher Education, 2009b, 2013a; Hasgall et al., 2019; Sowell et al., 2008), as well as the proportion of students who drop out (Council on Higher Education, 2009b, 2013a; Sowell et al., 2008).

These calculations will briefly be introduced below as an overview of different ways in which success is measured (i.e., graduation rate, throughput, student dropout, and time to completion), before illustrating the results found in the literature on student success. The focus of this study is, however, exclusively dedicated to the time to completion of students given that it is not a cohort-based measurement, and is linked to the discussion around efficiency, as presented above.

2.3.1. Student success measures

The **graduation rate** is briefly introduced, given its wide use in the South African higher education sector (Department of Higher Education and Training, 2019). The graduation rate is a relatively simple calculation that divides the total number of graduates within a particular academic year by the total number of students enrolled for the same year (Figure 2), typically for similar qualification types (Council on Higher Education, 2009b; Department of Higher Education and Training, 2019). This figure, represented as a percentage, can also be calculated across various available biographic information (as a representation of progress or success of transformation within the higher education system) or institutional information for comparative purposes (Council on Higher Education, 2009b). The calculation for graduation rates is relatively unique to the South African context (Department of Higher Education and Training, 2019), although Palmer (2016) noted that a similar calculation, referred to as ‘completion ratios’, is utilised in Australia. However, merely adding the total number of graduates would not clarify the amount of time invested in their training (Council on Higher Education, 2009b). The measure may thus be more accurately interpreted as growth or reduction within the sector, rather than success, and is dependent on the enrolment numbers and qualification length (Palmer, 2016). Since the graduation rate is calculated by adding headcount enrolments and graduates of the same academic year together, different cohorts are represented, and the calculation is sensitive to changes in enrolment figures. Graduation rates thus cannot distinguish between students who take different lengths of time to complete. As such, it is not considered further here.

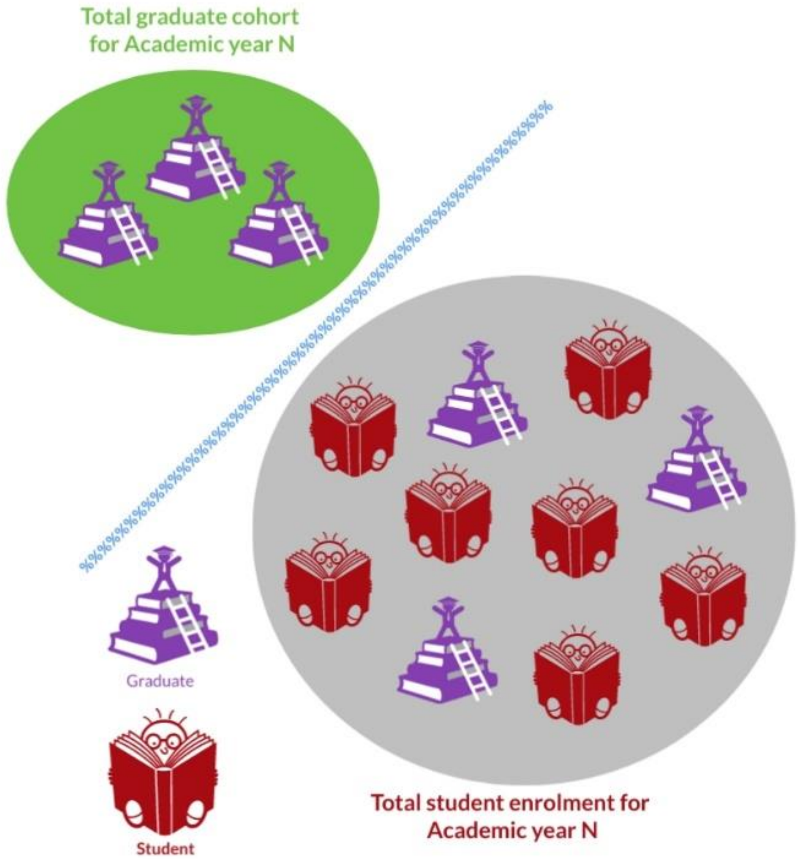

Figure 2: Graduation rate

Source: Author (Visme)[14]

Throughput, in contrast, is represented as that percentage of students who completed their qualification in the minimum time, from a particular cohort (a group of students who enrolled for their qualifications in the same year) (Department of Higher Education and Training, 2019). Throughput provides a relatively concise overview of the proportion of students who qualified within specific timeframes (Figure 3). Multiple years are typically presented to provide a cumulative perspective that suggests the time it takes to complete a qualification for the cohort (Van Lill, 2019). Throughput rates are typically calculated for the qualification minimum time, as well as two years thereafter, whereas completion

[14] Visme is an online platform developed to simplify the creation of infographics (https://www.visme.co/)

rates[15] are typically calculated similarly for several academic years. The throughput measure also indicates the number of students who are still enrolled, or who have (presumably) dropped out (those who have not yet graduated and are not currently enrolled). As such, the throughput measure of a given qualification can be used to compare different qualifications and institutions across similar qualification types (Council on Higher Education, 2009b; Watson, 2008). However, the focus of the measurement is on students who have completed their studies; thus, student dropout also needs to be considered as a possible outcome.

Figure 3: Throughput

Source: Author (Visme)

Student dropout, also referred to as attrition, can be defined within the current discussion, as an indication of the number or proportion of students who leave their qualifications without completing (Figure 4) (Department of Higher Education and Training, 2019; Jiranek, 2010). There is widespread difficulty in measuring student attrition within higher education. Two reasons for the difficulty in measuring dropout are that: first, students do not necessarily inform their institution that they have left; and second, that they may discontinue their studies temporarily and recommence to complete at a later date (referred to as stop out) (Figure 5) (Ampaw & Jaeger, 2012; Jiranek, 2010; Sowell et al., 2008). As a result, dropouts are typically assumed when students have not yet completed their qualifications, but have not re-registered in the academic year of

[15] The term completion rates, as used here, differs from the formal definition, as set out by the Department of Higher Education and Training (2019), however it is consistent with research that focuses on student success (Van Lill, 2019).

interest. This can typically only be confirmed in the longer term (after several years of non-completion or failure to re-register) (Palmer, 2016). Given the assumptions that are made, it becomes difficult to distinguish between students who received partial training and who would not qualify and those who would take longer than expected (Jiranek, 2010); or changes to a different qualification or institution (Sowell et al., 2008).

Figure 4: Dropout

Source: Author (Visme)

Figure 5: Stop out

Source: Author (Visme)

Merely calculating the number of students who complete a qualification does not readily provide information about how long it takes students to graduate. The **time to completion** for a master's – and doctoral qualification in particular – has therefore become an important measure of success, and is a focus both nationally (ASSAf, 2010; Mouton, 2007; Van Lill, 2019; Zewotir et al., 2015) and internationally (Agné & Mörkenstam, 2018; Geven et al., 2018; Hasgall et al., 2019; Horta et al., 2019; Jiranek, 2010; Sowell et al., 2015; Van de Schoot et al., 2013; Wamala & Oonyu, 2012). The time to completion is calculated by subtracting the end date from the start date to estimate the time it takes for students to progress through their academic journeys (Council on Higher Education, 2009a; Palmer, 2016). However, extant studies have difficulty specifying which dates signal each event (Palmer, 2016; Torka, 2020). The qualification commencement is recorded as the first enrolment date on which it is assumed that students start their academic journeys. However, some institutions may expect students to enrol with developed, or partially developed proposals (Connell & Manathunga, 2012; Torka, 2020) The development of proposals before formal enrolment would thus not officially be considered with the enrolment date. The enrolment date is likely the most accurate starting point for a measure of time to completion that is consistently recorded.

The date used to signal qualification completion proves slightly more challenging to select. Graduation dates represent the conferment of the qualification, which is ultimately the outcome of each qualification. However, the graduation date includes the time allocation for administrative processes to be completed (Spronken-Smith et al., 2018; Watson, 2008). This can extend completion times, and resides outside the control of both supervisors and students (Watson, 2008). Other dates that may provide consistent completion events may also include the submission of the thesis for examination (Agné & Mörkenstam, 2018; Palmer, 2016; Wamala & Oonyu, 2012), or the receipt of the results (Palmer, 2016; Torka, 2020), where authors likely utilise the most accurate measure available to them at the time.

Furthermore, often only the completion and commencement years are used in such calculations. These do not take into account students who register later in the year, or those who complete their studies at the beginning or middle of an academic year. The aggregation of a full year may over- or underestimate the completion times of students (Watson, 2008), thus calculating the time to completion in months may provide more accurate estimations (Palmer, 2016; Wingfield, 2011). Once the time to completion has been calculated, the measure may be comparable between different qualifications of the same type, and between different departments or institutions. In addition, the qualification minimum time may be subtracted from the measure to provide a comparison for qualifications with different minimum time allocations (Palmer, 2016). Such measurements provide a possible way in which to indicate efficiency.

The measures discussed above provide useful indications of how success may be considered in master's and doctoral training, although it ought to be mentioned that these measures are susceptible to a 'recency effect' (Palmer, 2016). Qualifications monitored more recently may not have all of their data available at the time of analysis and would seem lower than preceding cohorts (Palmer, 2016; Spronken-Smith et al., 2018). Thus, it may take several years to provide a robust analysis of a particular cohort. This does not preclude using these measures to track students' training and educational experiences. The following section will provide a brief overview of some national and international results regarding each of the measures discussed above.

2.3.2. Throughput

Master's and doctoral throughput measurements in South Africa (Table 1) show that very few students complete their qualifications in the minimum time (Essop, 2020; Van Lill, 2019; Watson, 2008).[16] Fewer than 10% of master's students complete their qualifications within one year (Essop, 2020; Watson, 2008). Completion rates for master's tend to increase from the second- and third-year of study, however, ultimately around 60% of master's are completed after six years of study (Essop, 2020; Watson, 2008). Doctoral candidates seem to have comparably lower completion rates, with between 10% and 20% completing their studies within three years (Essop, 2020; Watson, 2008). Ultimately, around half of doctoral candidates completed their studies within six years (Table 1), whereas Van Lill (2019) found the average seven-year completion rate to be 42.2% between 2000 and 2014.[17]

[16] Essop (2020) presented results of master's by research as a three-year qualification instead of a one-year qualification. As such, the statistics does not provide an indication of minimum time, but rather of N+2 as the first available data to compare.
[17] Van Lill (2019) utilised HEMIS data of enrolled and graduated doctoral candidates between 2000 and 2014, and thereby was able to combine the calculations for 15 student cohorts, resulting in an average score.

Essop (2020) disaggregated the completion rates between master's (by research and coursework) and doctoral qualifications by institution type. The study showed a remarkable improvement in the throughput of master's and doctoral students who first enrolled in 2008 and 2012. While completion within the minimum time remained low, students registered in 2012 were between 5-8% more likely to complete than the cohort for 2008 (ibid.). Nonetheless, the final completion rates suggested that there was room for substantial improvement (Essop, 2020).

Essop (2020) further compared different institution types, which allowed for the comparison of national completion statistics with that of Unisa (the only ODeL institution in South Africa). Despite showing substantial improvement between the 2008 and 2012 cohorts (Table 1), the completion rates for Unisa tended to be lower when compared to the national statistics for each qualification type. Of the students who enrolled for a master's by coursework qualification in South Africa, 9% completed within the minimum time, compared to 5% of Unisa students who completed within the minimum time. Of students who enrolled for a master's by research (unstructured) degree, 39% completed within the first three years, more than the proportion of Unisa students (31%), who completed during the same time. In contrast, a higher proportion of Unisa doctoral candidates completed in three years (23%), compared to the national average (18%). Although across six years, just above 40% of the Unisa students completed their studies, where the national scores ranged between 50% for doctoral candidates and just under 60% for master's students.

Table 1: Throughput rates of South African master's and doctoral students

Year(s)	Study level	Qualification	1-year	2-years	3-years	4-years	5-years	6-years	7-years	Source
Multiple 1993 - 2005	Master's by coursework and research report	Full-time**	4%	35%	54%	59%	-	69%	-	(Watson, 2008)*
		Part-time**	-	9%	21%	34%	38%	-	43%	
	Master's by dissertation	Full-time**	2%	14%	36%	51%	-	57%	-	
		Part-time**	-	9%	25%	32%	43%	-	45%	
	PhD	Full-time**	-	1%	10%	24%	42%	-	55%	
		Part-time**	-	-	-	16%	27%	30%	31%	
2008	Master's Degree (Coursework) (N = 1)	Unisa	3%	5%	16%	21%	25%	28%	-	(Essop, 2020)
		Total	7%	22%	34%	42%	47%	50%	-	
	Master's Degree (Research) (N = 3)	Unisa	-	-	15%	23%	31%	35%	-	
		Total	-	-	36%	45%	51%	54%	-	
	Doctoral Degree (N = 3)	Unisa	-	-	14%	18%	24%	29%	-	
		Total	-	-	16%	28%	39%	46%	-	
2012	Master's Degree (Coursework) (N = 1)	Unisa	5%	8%	24%	32%	37%	40%	-	
		Total	9%	25%	40%	49%	55%	58%	-	
	Master's Degree (Research) (N = 3)	Unisa	-	-	31%	38%	43%	45%	-	
		Total	-	-	39%	49%	55%	59%	-	
	Doctoral Degree (N = 3)	Unisa	-	-	23%	32%	38%	43%	-	
		Total	-	-	18%	32%	43%	51%	-	
Multiple 2000 - 2014	Doctoral Degree (N = 3)	National average	-	-	-	25%	34.3%	39.3%	42.2%	(Van Lill, 2019, p. 180)

* The studies within this table reported the results concerning the minimum time (i.e. N; N+1; N+2; N+3). Given that the presented results held different assumptions for the minimum time each, the results were converted to the number of academic years studied. The result of Watson (2008) included the largest minimum time and up to N+7 years, including a 'poss. max' estimation. The results that presented completion between eight and eleven years (in addition to the 'poss. max') could not be fitted to the table. The study used multiple cohorts in the data estimations, which does not present a continuous calculation of a single cohort. Results were not presented for N+4 nor N+6.

** Master's: Full-time (N = 1); Part-time (N = 2). PhD: Full-time (N = 2); Part-time (N = 4).

Findings from the South African context seem somewhat lower, although comparable to those reported internationally. Completion rates within the US were found to be as low as 7.1%-10.5% after four years of study; and reach, on average, 45.5% over seven years (Sowell et al., 2008), seemingly with a limit of 50% (Ampaw & Jaeger, 2012) and 56.6% across ten years (Sowell et al., 2008). Within another study, completion rates were found to be 45% (Zhou & Okahana, 2019). Whereas, for underrepresented minorities in the US, 44% of the doctoral candidates completed within seven years (Sowell et al., 2015). Around 20% of the students remained enrolled in these programmes after seven years (Sowell et al., 2015). Data from Europe indicated a higher completion rate, with 66% of the student completing a doctorate within six years. Although this rate was not found to be stable between countries, for the most part, it seemed to remain constant across time (Hasgall et al., 2019). Within the Netherlands, it has been found that doctoral completion rates are typically around 75%. However, it is noteworthy that, in the Netherlands, doctoral candidates are treated as university employees (Van de Schoot et al., 2013). Outside of Europe, New Zealand found completion rates between 73% - 86% for cohorts who started between 2000 – 2008 (Spronken-Smith et al., 2018),[18] and Australia seemed to have completion rates between 65% - 75% over nine years (Torka, 2020). It is worth noting that 50% of the students (estimated)[19] in the Australian study completed their doctoral qualifications within five years (Torka, 2020).

Student throughput places the focus on students completing their qualifications. However, as indicated above, the proportion of students who complete their studies in minimum time tend to be in the minority. Ultimately a large proportion of the students may not complete their master's or doctoral education. The following section thus presents attrition statistics that may indicate loss during the education process. This presents an alternative measurement to contextualise the discussion around the completion of master's or doctoral qualifications.

[18] The institution where the study was conducted provided additional support to their students, which anecdotally assisted in increasing the completion rates (Spronken-Smith et al., 2018).
[19] The completion rates needed to be estimated from graphical presentations and were not explicitly recorded in the article text.

2.3.3. Student dropout

An analysis conducted by Watson (2008) suggests that the highest probability of student dropout was during the minimum time for a particular qualification. Similarly, Mouton (2011) found that the largest proportion of dropouts occurred in the first two years of study (29%). Interpreting these findings, Watson (2008, p. 736) noted that "students who remain registered after this period are likely, at some point, to subsequently graduate" (2008, p. 736). Within the context of South Africa, Mouton (2011) estimated doctoral dropouts to be around 46% of those who enrolled in 2001.

Mouton (2011), however, argued that the dropout statistics were also comparable to dropout numbers internationally, specifically in the US. This finding provides some corroboration to the claim, made by ASSAf (2010), that this was a universal problem. Golde's (2005) synthesised various sources to estimate doctoral dropouts to be between 40 - 50% in the US, while Sowell et al. (2015) estimate that dropouts across seven years reach 36%. Dropout estimates within the US across ten years were between 30.6% (Sowell et al., 2008) and 50% (Ampaw & Jaeger, 2012),[20] where the largest proportion of dropouts occurred during the start of the qualification, rather than later years (Ampaw & Jaeger, 2012; Sowell et al., 2008), similar to the findings presented by Watson (2008) and Mouton (2011) above. In this instance, students who dropped out after the first or second year of study tended to leave with a master's-level qualification (Sowell et al., 2008). In Australia, Jiranek (2010, p. 10) indicated that up to a third (33%) of doctoral candidates do not complete within five years (interpreted by the author as "an apparent attrition rate"). In Spain, the dropout rates were estimated to be as high as 70 - 90% (De Miguel Díaz, 2010, as cited in Castelló et al., 2017).[21] By way of contrast, in New Zealand, the dropout rates were comparatively low (16% for cohorts who registered between 2000 and 2008) (Spronken-Smith et al., 2018), possibly indicating a larger problem in some countries when compared to others.

The abovementioned measures that calculate completion or dropout typically provide headcount statistics or proportions represented through percentages. Although for those

[20] The study was conducted at a single institution.
[21] The original article was not available in English: De Miguel Díaz, M. (2010). Evaluación y mejora de los estudios de Doctorado PhD assessment and improvement. Revista de educación, 352, 569-581.

who graduate, it is not always clear how long students typically take to complete their studies. Students can complete at any point during an academic year, where the entire year is still used in the calculations. It is impossible to distinguish between students who complete at the beginning of a new academic year or who utilise the entire registration period to complete their studies. It thus becomes necessary to consider the time between the first registration and completion to provide a more accurate comparison.

2.3.4. Time to completion

As indicated within the throughput rate calculations, few students typically manage to complete within the minimum timeframe (ASSAf, 2010; Essop, 2020; Mouton, 2007; Van de Schoot et al., 2013; Van Lill, 2019; Watson, 2008), and on average, doctoral students take just under five years to complete their qualifications (ASSAf, 2010; Mouton, 2007; Van Lill, 2019). Van Lill (2019) found that, between 2000 and 2014, the average time to completion for South African doctoral studies ranged between 4.3 years and 4.9 years, with an average of 4.7 years between 2012-2014.[22] For master's qualifications, Zewotir et al. (2015) found that between 2004 and 2011, the modal completion time for master's students was two years. The available graphical information suggests that these students' average completion time would be closer to 2.8 years (Zewotir et al., 2015).[23] In comparison, the previous findings presented by the CHE indicated that master's students typically take up to three years to complete their studies (Council on Higher Education, 2009a).

Although a comparison to the average time to completion within international institutions is made with caution, due to differences in qualifications structures, the time to completion of South African doctoral candidates was in line with the average expected times abroad (Council on Higher Education, 2009a; Mouton, 2007; Watson, 2008). Findings in Africa from Uganda suggested that master's qualifications were estimated to take a median of

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[22] Van Lill (2019) calculated the average time to completion by removing all doctoral records with a completion time of less than two years, and more than 15 years, respectively.

[23] Due to the timeframe within which the study was published, completion times for master's students were capped at seven years of registration, which may lower the average completion time for students as a whole (Zewotir et al., 2015).

47 months (3.8 years), ranging between 21 months (just under two years) and 71 months (just under six years) (Wamala & Oonyu, 2012). Students take about five years to complete their doctoral qualifications, which is longer than the required three years, according to their educational system (Wamala & Oonyu, 2012). In Europe, Hasgall et al. (2019) reported that candidates typically take between 3.5 and 4.5 years to complete their doctoral studies. The median time to completion for a doctoral degree in Portugal was five years, whereas students typically complete between four and six years (Horta et al., 2019). The research focused on the Netherlands suggests that doctoral candidates complete their qualifications in an average of 60 months (5 years) (Van de Schoot et al., 2013).

Similarly, doctoral candidates typically take around five years to complete their studies outside Africa and Europe. Studies suggest that the time to completion in the US is around five years (Sowell et al., 2015) or just below six years (5.76 years) to complete their doctoral qualifications (Zhou & Okahana, 2019). In comparison, the completion time was around five years in Australia (Jiranek, 2010; Sinclair, 2004; Torka, 2020) and around 4.4 years in New Zealand (Spronken-Smith et al., 2018). Corroborating the arguments made in previous studies that the time to completion for South African doctorates was comparable to those found abroad (Council on Higher Education, 2009a; Mouton, 2007; Watson, 2008).

As previously discussed, this study focuses exclusively on the time to completion of master’s and doctoral students as a measurement of success. This measurement is used to investigate if students take longer than expected to complete their studies, which is represented in the efficiency argument (discussed in section 2.3). Although the measurement only considers students who have completed their qualifications successfully, determining which factors influence students’ time to completion would assist in the development of more effective support interventions for supervisors and master’s and doctoral students.

Unlike the throughput and dropout statistics presented above, the time to completion isn’t cohort based (depending on the number of enrolments in a particular year) and can be calculated for individual students. This measure thus provides an interval level scale due to the length of time spent on their studies rather than the binary ‘completed’ versus ‘not completed’ category. This provides a larger possible sample size, given that it would not matter when students first enrolled, and can be compared or combined across different enrolment years. In contrast, throughput requires that the measurement is calculated for a cohort as a group within a particular academic year.

Although it is possible to investigate the levels of success, as indicated by each of the measures above, such an analysis does not provide information on what factors may influence student success in master’s or doctoral education. The section below will provide an overview of how various factors influence students’ academic journeys, and what factors may be considered when investigating possible ways of improving master’s and doctoral training in higher education.

2.4. Factors influencing student success

With the expanding research on master’s and doctoral education, authors have further attempted to identify factors that influence students’ success (Agné & Mörkenstam, 2018; Jiranek, 2010; Sowell et al., 2015; Spaulding & Rockinson-Szapkiw, 2012; Spronken-Smith et al., 2018; Van de Schoot et al., 2013; Van Lill, 2019; Wamala & Oonyu, 2012; Zewotir et al., 2015), or dropout (ASSAf, 2010; Castelló et al., 2017; Gardner, 2009; Leijen et al., 2016; Sowell et al., 2015; Sverdlik et al., 2018; Van Lill, 2019; Zewotir et al., 2015) during master’s and doctoral education. Horta et al. (2019) have described the focus area of identifying factors that affect students’ time to completion as an area of research that has been overlooked. Identification of such factors may assist in developing more effective training models or support systems to increase student success and reduce student attrition (ibid.). The factors identified in previous studies are divided into four broad categories in the discussion below, namely: demographic factors; institutional factors; situational factors, and student dispositions (Van Lill, 2019).

Demographic factors within the discussion below include students’ gender, race, age, and nationality (Agné & Mörkenstam, 2018; Jiranek, 2010; Sowell et al., 2015; Spronken-Smith et al., 2018; Van de Schoot et al., 2013; Van Lill, 2019; Wamala & Oonyu, 2012; Zewotir et al., 2015). It is assumed that such variables act as proxies, rather than represent innate abilities, and differences attributed to these variables may thus indicate possible structural biases within training programmes or educational contexts (Agné & Mörkenstam, 2018). The data is also typically readily available within institutional databases.

Institutional factors within this project would refer to variables that are similarly available from institutional systems, which describe a particular qualification or educational structure (ASSAf, 2010; Geven et al., 2018; Jiranek, 2010; Sowell et al., 2015; Spronken-Smith et al., 2018; Sverdlik et al., 2018; Van Lill, 2019; Wamala & Oonyu, 2012; Watson, 2008; Zewotir et al., 2015). The factors of interest discussed in this chapter include the influence of the programme discipline, or whether a qualification includes a coursework component.

Situational factors are typically more unique to each student. For instance, whether they have funding available, or whether they studied on a full-time or part-time basis (ASSAf, 2010; Agné & Mörkenstam, 2018; Castelló et al., 2017; Geven et al., 2018; Jiranek, 2010; Leijen et al., 2016; Spronken-Smith et al., 2018; Sverdlik et al., 2018; Van Lill, 2019; Wamala & Oonyu, 2012; Watson, 2008; Zewotir et al., 2015).

Finally, **dispositional factors** are concerned with the attitudes, abilities, or skills of students (ASSAf, 2010; Castelló et al., 2017; Gilmore et al., 2016; Herrmann & Wichmann-Hansen, 2017; Leijen et al., 2016; Sverdlik et al., 2018; Van Lill, 2019). In addition to measurements of student satisfaction, or motivation, which HEIs may not typically collect, that would influence students' progress during their academic journeys (Van Lill, 2019). A brief overview of previous research is expanded in the following sections in order to outline possible factors that may influence student success.

2.4.1. Demographic factors

Demographic data is available in institutional systems and are used for statutory reporting (Council on Higher Education, 2019), providing a possible area for authors to investigate. Such investigations are typically instrumental in demonstrating the effectiveness of transformation efforts across time within the higher education sector (Herman, 2017).

However, as illustrated below, they demonstrate ambiguous results regarding the effects of these variables on student success. Below is a short outline of these variables, including gender, race, age, and nationality.

Literature investigating the effects of **gender** or **race** on student success presents somewhat ambiguous results. As previously discussed, the time to completion for doctoral studies was, on average, five years (ASSAf, 2010; Agné & Mörkenstam, 2018; Council on Higher Education, 2009a; Jiranek, 2010; Sowell et al., 2015; Spronken-Smith et al., 2018; Van de Schoot et al., 2013), whereas master's students typically completed in three years (Council on Higher Education, 2009a). By way of comparison, completion times differed by months, which may have been statistically significant in some studies, but not large enough to be of practical use. Such significant differences in the time to completion of students ranged between one and six months in different studies (ASSAf, 2010; Council on Higher Education, 2009a; Jiranek, 2010; Sowell et al., 2015; Van Lill, 2019). Although in the abovementioned examples of gender differences, male students tended to complete in slightly less time compared to female students, Van Lill (2019) found that these differences seemed to alternate depending on the discipline studied. Female students took five to seven months longer than their male peers to complete qualifications in Electrical engineering and Sociology. However male students took between 0.24 and two months longer than female students to complete their qualifications in Education, Clinical health sciences, and Physics (Van Lill, 2019). In contrast, such differences were not found in other studies with regard to gender (ASSAf, 2010; Agné & Mörkenstam, 2018; Council on Higher Education, 2009a; Spronken-Smith et al., 2018; Van de Schoot et al., 2013; Wamala & Oonyu, 2012; Zewotir et al., 2015), or race (Van Lill, 2019). In studies on the time to completion of master's students, similar small differences between one month and four months were found across gender and race (Council on Higher Education, 2009a).

The completion rates and dropout of students were similarly ambiguous according to gender and race. One group of studies did not find significant gender differences according to completion rates (Ampaw & Jaeger, 2012; Torka, 2020). In contrast, in another group of studies, completion rates differed slightly across seven years for gender

(3%) and race (7%) (Sowell et al., 2015; Spronken-Smith et al., 2018). However, Ampaw and Jaeger (2012) found that differences attributed to race depended on which stage of education students were in. The dropout rates for students were similarly measured to differ by between 3% - 7% (Sowell et al., 2015; Spronken-Smith et al., 2018), or did not find any difference in the drop out by gender or race (Zewotir et al., 2015).

In terms of the students' **age**, those who started their educational journeys when they were younger (below 30) seemed to complete their studies in less time (on average between one and 2.5 years) compared to those who were older (above 50 or 60) in both master's and doctoral education (ASSAf, 2010; Council on Higher Education, 2009a). By way of contrast, students between these ages (above 30 and below 50) seemed to consistently complete their studies within the previously reported average time for their qualification types, representing a smaller difference compared to the two extreme groups above (ASSAf, 2010; Council on Higher Education, 2009a). Although Zewotir et al. (2015) found that age correlated with the time to completion of master's students, some studies did not find a significant relationship between time to completion and student's age at registration (Jiranek, 2010; Spronken-Smith et al., 2018; Wamala & Oonyu, 2012). Whereas, findings by Van Lill (2019) suggest that age differences were not consistent across disciplines, and where these were measured, only accounted for three to six months. The age of students also didn't seem to impact their likelihood of dropping out (Ampaw & Jaeger, 2012; Zewotir et al., 2015), although the ASSAf (2010) study found a relationship between age at enrolment, in combination with familial or professional commitments, and dropout.

Studies that compare the completion time of students across different **nationalities** (domestic or foreign) suggest that international students (irrespective of which country hosted the qualification) tend towards shorter completion times (Agné & Mörkenstam, 2018; Ampaw & Jaeger, 2012; Horta et al., 2019; Jiranek, 2010; Spronken-Smith et al., 2018; Torka, 2020; Van Lill, 2019; Wamala & Oonyu, 2012; Zewotir et al., 2015). The difference in completion times between domestic and international students varied between studies and ranged from differences that were not statistically significant (Van Lill, 2019), to larger differences of four months (ASSAf, 2010) and six months (Jiranek, 2010; Spronken-Smith et al., 2018; Torka, 2020), or up to two years (Agné & Mörkenstam, 2018). One explanation for lower completion times for international students was that these students would be under pressure to comply with visa or funding requirements (Jiranek, 2010; Torka, 2020).

Similarly, international students were more likely to complete their studies, albeit with a small effect. International students were 1% - 2% (Cloete et al., 2015; Spronken-Smith et al., 2018), or 4% - 5% (Torka, 2020) more likely to complete their studies. It ought to be noted that the difference, as a result of nationality, was comparatively small, and that the studies differed drastically in the overall proportion of students who completed. The study by Cloete et al. (2015) presented completion rates of South African students which differed between 45% and 47%. A study by Spronken-Smith et al. (2018) presented findings from New Zealand, which indicated a difference between completion rates of 83% and 84%, whereas Torka's (2020) study was conducted in Australia, with estimated completion rates of up to 80%. In contrast, there seemed to be no effect regarding student dropout in terms of nationality (Zewotir et al., 2015).

Overall, the results from previous studies suggest that demographic variables have an ambiguous effect on students' success. A multiple regression model, which included gender, academic discipline, race, age, registration status, and nationality, only explained 8% of the variances present within the doctoral student's time to completion, as measured by Van Lill (2019). Where differences or relationships with demographic variables were found, such differences typically accounted for an average of a few months in study time. Furthermore, demographic variables seemingly act as proxies for other effects, likely related to how the higher education systems are structured (Agné & Mörkenstam, 2018). It is thus crucial to consider variables outside the demographic distribution of students, so as to identify possible barriers to learning that can be remedied, or provide indications for possible intervention.

2.4.2. Institutional factors

As for demographic variables, aspects of the qualifications (discipline and coursework structures) have been investigated to determine possible avenues to improve student success. Such variables typically relate to the qualification structure introduced as part of the HEQSF, and may not present immediate changes. Similarly, differences that may have resulted from the unique characteristics of the institution would also take considerable time to change. However, long-term improvements can be derived from such investigations, and remedial avenues may also be presented.

One such variable which seems to have drawn considerable attention is the **discipline** within which students conduct their research. Disciplines typically share research approaches, career focus, resource requirements, and institutional or infrastructure support needs (Herman, 2017). Research that investigated the completion time of students seems to find some differences due to disciplinary focus (Jiranek, 2010; Sinclair, 2004; Sowell et al., 2015; Van Lill, 2019; Wamala & Oonyu, 2012). However, as described by Zewotir et al. (2015, p. 6), disciplinary influence on results has varying levels of success. Studies may show conflicting results, where a discipline that takes longer in one study may be completed in comparably less time in a different study (ASSAf, 2010; Sinclair, 2004; Sowell et al., 2015; Spronken-Smith et al., 2018), where similar conflicting results appear to be presented for completion rates (Van Lill, 2019; Watson, 2008).

The differences in the time to completion of students were typically less than a year and ranged between four months and eleven months (ASSAf, 2010; Council on Higher Education, 2009a; Jiranek, 2010; Van Lill, 2019).[24, 25] Some studies did find differences that were between one year, to a year and five months (Sowell et al., 2015; Zhou & Okahana, 2019). However, differences between disciplines seemed to be primarily between two extremes in each comparison, whereas differences in the time to completion between most disciplines tended to be more moderate (Council on Higher Education, 2009a). One difficulty with the abovementioned comparisons is that the disciplinary comparisons across studies may not be equivalent, and authors may use different assumptions when grouping disciplines together.

[24] One of the disciplines included an estimate of 5.3 years of study, however, this was based on only four records (Jiranek, 2010), and thus not used within the description presented here.
[25] Excluding cases with completion times less than two years, or more than 11 years (Van Lill, 2019).

In contrast to the time to completion, there seemed to be more considerable differences in the completion rates between disciplines in the long term (Van Lill, 2019). The completion rates reported in various studies differed by 14% to 27% across seven years (Sowell et al., 2008, 2015; Spronken-Smith et al., 2018; Torka, 2020; Van Lill, 2019). The 10% differences measured across broader STEM versus non-STEM disciplines was comparably smaller (Zhou & Okahana, 2019), while the attrition rates of students also showed differences across disciplines between 10% and 14% (Sowell et al., 2015; Torka, 2020).

As discussed above, comparing results that indicate disciplinary differences across studies becomes difficult, and such differences may not be consistently measured. Disciplinary differences may, however, act as proxies for access to resources such as funding or institutional affiliation. Van Lill (2019) notes that the differences between disciplines in completion rates (and presumably attrition rates) may also partially be explained by institutional focus, where some universities in South Africa enrolled more doctoral students in specific disciplines. Watson (2008) also argues that the differences between disciplines may instead result from specific institutions. In other studies, the effects of different disciplines could have been influenced by the unequal proportion of foreign students (Zhou & Okahana, 2019), or part-time students (Spronken-Smith et al., 2018) in the different disciplines.

The review conducted by Sverdlik et al. (2018) illustrated that ‘professional programmes’, which include **coursework** and a research component, may benefit students. It was suggested that the coursework structure provides a gradual learning approach for the cohort of students that also assists in integrating them within their departments. Previous studies also found that more structured educational programmes seemed to increase student success (Geven et al., 2018; Naidoo, 2015). Watson’s (2008) results indicated that the seven-year completion rate for full-time coursework master’s students was 7% higher than full research master’s qualifications. However, only a 1% difference was found for part-time students in the two qualification types. Watson (2008) argues that including generic coursework content may add to students’ workloads, and not provide the required research support they need. Rather such a coursework component should preferably be designed around the research project of students (Watson, 2008). More research is needed to provide more comprehensive evidence (Sverdlik et al., 2018; Watson, 2008).

Differences in the time to completion between **institutions** also seem apparent, but variable. In comparing South African universities, the CHE (2009a) provided an overview of the time to completion between institutions for both master's and doctoral students who studied in 2005. As previously presented, master's students typically took about three years to complete their studies, where doctoral candidates took just under five years. For master's students, the average completion time across institutions was 2.9 years, which ranged between 2.2 years,[26] and 3.8 years to complete their studies. For doctoral candidates, the time to completion ranged between 3.9 and 5.3 years, although the average completion time was above five years for only two institutions. The overall average time to completion for doctoral candidates was 4.7 years. For Unisa in particular, the time to completion was reportedly 3.8 years for master's students, and 4.8 years for doctoral candidates. Thus, master's students seemed to take close to a year longer than the overall national average, whereas, for doctoral candidates, the difference on average was about one month. Although such differences were seemingly apparent, Unisa shared similar completion times with other institutions for both qualification types, where longer or shorter completion times may not have resulted from the ODeL nature of Unisa's teaching model (Council on Higher Education, 2009a). Internationally, differences were also found between students' time to completion (Horta et al., 2019) and completion rates compared across different institutions (Torka, 2020), which may have been linked to the available resources of the institution. Torka (2020) noted that policy changes and different institutional factors seemed to result in shrinking differences in success rates between institutions.

[26] The University of the Western Cape (UWC) reportedly had an average of one year for master's students (Council on Higher Education, 2009a), however, it is not known whether or not this was the result of institutional limits on the time to completion of master's students.

2.4.3. Situational factors

The situational factors discussed in this section relate to students' access to funding, or whether they were registered as full-time or part-time students. Previous research has found that available **funding** tended to assist students in completing their studies, when compared to students who were financing their own studies (Agné & Mörkenstam, 2018; Geven et al., 2018; Jiranek, 2010; Van Lill, 2019). By way of contrast, a lack of financial support has increased student dropout or dropout considerations (ASSAf, 2010; Castelló et al., 2017; Sverdlik et al., 2018; Van Lill, 2019). Given that students typically report lacking the necessary resources, specifically financial support (Jones, 2013), student funding seems to act as a substantial barrier to completing a master's or doctoral degree.

In terms of completion time, students who had access to funding seemed to complete their studies in less time when compared to those who did not have access to financial resources. This effect was seemingly moderate in some studies, with an average difference of six months (Spronken-Smith et al., 2018), however, there were also more substantial differences in completion times, of nearly two years to two-and-a-half year difference in other studies (Agné & Mörkenstam, 2018; Jiranek, 2010). The findings by Agné and Mörkenstam (2018) also highlighted the importance of having funding available from the outset of a qualification, as opposed to gaining access to funding at a later time. In contrast, Wamala and Oonyu (2012) presented results that do not support such a claim, where no significant relationship was found with being externally funded.

Students who had access to funding were also more likely to complete their studies compared to students who did not. Differences in completion rates showed that students with access to funding were 6% more likely to complete (Spronken-Smith et al., 2018), whereas larger differences in completion rates between 16% and 23% were found by Torka (2020). Students who ultimately lost their financial support were also comparatively more likely to complete their studies, which was interpreted as a possible selection bias of students who were able to secure funding, or that students may have been more motivated, since they had already made use of study funds (Torka, 2020).

In contrast to the typical findings that funding led to increased completion, Zewotir et al. (2015) found that master's students with funding available were 15% more likely to drop out than those without funding. According to findings presented by Zewotir et al. (2015), both time to completion and time to dropout were shortened when students had funding available for their studies. This may indicate the possible influence of funder requirements, pressures for students to perform, or their willingness to continue their studies (Zewotir et al., 2015). If students take longer than expected and lose their funding, they may not be in a position to continue with their studies (Zewotir et al., 2015). Further contradictory findings included that doctoral candidates in Portugal tended to take slightly longer to complete their studies (by a semester) if they received funding than students who did not (Horta et al., 2019).

Leijen et al. (2016) conducted interviews and indicated that student funding often does not cover the cost of living. As a result, students cannot afford living costs that allow them to study if they are not simultaneously employed. This possibly implies that they would also be unable to afford their studies on their salaries without gaining access to postgraduate funding (Horta et al., 2019; Leijen et al., 2016). In such a way, funding may be both incentive and a barrier to student success (Greene, 2015). Students who do not receive enough funding, or do not receive funding, indicate that the lack of financial support acts as a barrier to their learning. In contrast, those who receive enough funding indicate that this has increased their ability to succeed in their qualifications (Greene, 2015). As such, the influence of student funding on completion rates and time to completion has been described as complex (Torka, 2020).

Whether students were registered for **full-time or part-time** studies arguably has an impact on their available time to spend on their studies. Students who cannot study full-time likely have additional responsibilities (such as employment) that take time and energy, which may affect student success (Herman, 2011; Kumar & Johnson, 2019; Leijen et al., 2016; Van Lill, 2019; Wingfield, 2011). Findings by Van Lill (2019) suggest that students who are not employed (and therefore presumably have the available time to study full-time) completed their research up to five months before their employed counterparts. Results by Spronken-Smith et al. (2018) suggest that this difference may be up to two years, where full-time students completed in less time compared to part-time students. Students who studied full-time also completed their studies in less time than students who changed from full-time to part-time studies by slightly more than a year (Spronken-Smith et al., 2018). In contrast, however, not all studies found a significant difference between time to completion and registration status (Wamala & Oonyu, 2012).

The completion rates for full-time students were between 16% - 29% higher than the completion rates for students studying part-time (Spronken-Smith et al., 2018; Torka, 2020; Watson, 2008). Higher completion rates were also found among students who changed between full-time and part-time studies, whose completion rates were 5% higher than students who were only enrolled full-time (Spronken-Smith et al., 2018). The findings may thus suggest that students' registration status (presuming the amount of time they have to commit to their studies) may substantially affect whether or not students finish their studies, rather than how long it takes.

In contrast, previous research in the US appears to show a benefit in terms of completion rates and time to completion for students registered for part-time studies (Ampaw & Jaeger, 2012). Ampaw and Jaeger (2012) argue that students registered for full-time studies might intentionally take more time to complete so as to delay possible unemployment. On the other hand, part-time students were already working, providing financial stability, and were already employed. In addition, students employed in research assistant positions were likely to have increased access to faculty and peers, suggesting that such positions provide additional benefits beyond financial resources (Ampaw & Jaeger, 2012). Implying that several factors simultaneously influence student completion.

2.4.4. Dispositional factors

Dispositional factors represent a broader range of possible variables typically related to more subjective influences on student success in master's and doctoral education. These may include studies that focus on the academic readiness of students, particularly related to conducting research (Castelló et al., 2017; Gardner, 2009; Gilmore et al., 2016; Spaulding & Rockinson-Szapkiw, 2012), or their ability to deal with pressure, and manage their emotions during the stressful time (Castelló et al., 2017; Gilmore et al., 2016; Herrmann & Wichmann-Hansen, 2017). Other studies included investigations into the socialisation or work-life balance of students, arguing that increased risk of dropout includes feeling isolated and a lack of social or academic integration (ASSAf, 2010; Castelló et al., 2017; Gilmore et al., 2016; Herrmann & Wichmann-Hansen, 2017; Naidoo, 2015; Schulze, 2011; Spaulding & Rockinson-Szapkiw, 2012; Sverdlik et al., 2018). For example, a respondent cited in Gilmore et al. (2016, p. 427) described doctoral studies as “a lifestyle”. In contrast, a participant for Spaulding and Rockinson-Szapkiw described their experience as follows: “The entire process was difficult. It takes up your entire life” (2012, p. 206). Other variables that have been considered include the role of self-efficacy (Schulze, 2011), self-regulation (Kelley & Salisbury-Glennon, 2016; Wagener, 2018), psychological attributes (Abdullah & Evans, 2012), the attitudes of students, and the role that motivation or finding a sense of meaning in their studies play in student retention (Castelló et al., 2017; Gardner, 2009; Gilmore et al., 2016; Greene, 2015; Marshall et al., 2017; Spaulding & Rockinson-Szapkiw, 2012; Spronken-Smith et al., 2018; Sverdlik et al., 2018), or the adverse effects of experiencing imposter syndrome, marked by feelings of inadequacy and lacking self-confidence in their work (Marshall et al., 2017).

Van Lill (2019) found that students who **considered dropping** out during their studies took almost four months longer on average to complete compared to those students who did not consider dropping out. At the same time, Marshall et al. (2017) noted that students whose completion was delayed also considered dropping out of their studies. However, it is unclear whether students’ delay increased their desire to drop out, or if students who felt like dropping out took more time to complete their studies.

As research within master’s and doctoral education has developed, some researchers also focused on **supervision influences**. Student **satisfaction with supervision** has been positioned as a potential indication of supervision support or efficacy and seemed to have a relation, albeit weak, to shorter completion times (Van Lill, 2019). Van Lill (2019) found that students who experienced dissatisfaction with their supervisors took, on average, just under six months longer to complete their studies compared to students who were satisfied with their supervisors. However, satisfaction studies typically collect data after students have completed and, as a result, represent their perceived experiences in retrospect. Students may be particularly satisfied or dissatisfied after the fact. However, such impressions may be strongly influenced by having completed their projects. Nonetheless, Sverdlik et al. (2018) argued that the impact of supervision relationships on doctoral student experiences is often cited as the most influential factor on how supervisors may impact their students' academic journeys, specifically that these relationships influence student persistence and achievement.

Murphy (2009) suggests that time to completion may be affected by students' **relationships with their supervisors**. This study indicated different expectations between students and supervisors, where students may prefer more directive approaches by supervisors, and supervisors, in turn, focus on developing students' independence. It is then presumed that differences in supervisors' preferred approaches may increase students' time to complete their studies (Murphy, 2009). Previous studies presented similar interpretations that students and supervisors may have different expectations within their relationships (Howells et al., 2017; Kandiko & Kinchin, 2012). If student or supervisor expectations remain unmet, they may result in negative supervision relationships (Howells et al., 2017). This is illustrated succinctly by the participant in Van de Schoot et al. (2013, p. 7), who experienced a delay of about two years, and indicated their frustration by stating: "HE'S LEFT ME ALONE" *[sic]*. In turn, some studies displayed a link between students' perceptions of their supervision relationships and their academic performance (De Kleijn et al., 2012; Sinclair, 2004; Wagener, 2018). The quality of supervisory relationships was influenced by the frequency with which they communicated with their supervisors (Wagener, 2018), as well as when they received feedback on their work (De Kleijn et al., 2014; Naidoo, 2015). Similarly highlighting the importance of supervisory relationships, one of Spaulding and Rockinson-Szapkiw's participants stated that: "[…] when you get to the dissertation phase, now it's more self-paced and it's you and your advisor, your main advisor, and that's it" (2012, p. 208).

In contrast, there are also examples where students seemed to have passed their qualifications despite their supervisors. However, even in such instances, supervision events were recognised as necessary for students' progress (Lessing & Schulze, 2002). Students thus not only need supervisors concerning the technical requirements of their qualifications, but also as sources of encouragement or emotional support (to feel as if their supervisor cares) (Benmore, 2016; De Kleijn et al., 2012; González-Ocampo & Castelló, 2019).

As a result, one of the risk factors identified for student attrition is a poor relationship between students and their supervisors (ASSAf, 2010; Leijen et al., 2016). **Supervision relationships** were the second most referred to theme when students were asked about the most positive or negative aspects of their doctoral studies, reiterating the importance of such relationships (ASSAf, 2010). According to Van Lill's (2019) findings, overall, 38% of the study sample indicated that a lack of supervision was a barrier to completion. Murphy (2009) demonstrated such an effect on a small scale, where students took up to six months longer to complete their studies due to their supervisory relationships. Arguably, Murphy's (2009) sample size only included 11 participants, and the difference of several months has already received a critical appraisal in previous sections.

Students may, however, feel they lose ownership of their studies if there is too much involvement or control from supervisors (De Kleijn et al., 2012; Herrmann & Wichmann-Hansen, 2017). The review by Sverdlik et al. (2018) cited a larger-scaled example by Lovitts (2001), where students who completed their studies were six times more likely to have **selected their supervisors** than their non-completing counterparts who were assigned supervisors. Students who were involved during the selection of supervisors seemed to have better integration within their research communities, and a higher level of confidence when their work was accepted by their supervisors (González-Ocampo & Castelló, 2019), making better progress and having a higher level of satisfaction with the supervision they received (Ives & Rowley, 2005).

Some studies suggest that students or supervisors could **adapt their approaches** to supervision relationships, even when they may be opposed to certain supervision practices (Kumar & Johnson, 2017, 2019; Murphy, 2009; Schulze, 2011). However, such adaptations may increase the frustration experienced within the supervision relationship, which may adversely affect time to completion (Åkerlind & McAlpine, 2017; Murphy, 2009). Research into supervision approaches recommends that open communication is the primary catalyst of relationship transformations (Cornelius & Nicol, 2016; Marshall et al., 2017; Sverdlik et al., 2018). It highlights the importance of supervision relationships in assisting or hindering student progress (Spaulding & Rockinson-Szapkiw, 2012; Sverdlik et al., 2018). Studies on the role of supervision relationships in successful completion are typically qualitative, where students or supervisors describe some of the difficulties they have experienced. In contrast, quantitative measures of the effects of the abovementioned experiences are not as readily available.

As illustrated throughout this section, a multitude of factors might influence student success, or act as proxy indicators representing underlying issues. This study does, however, not aim to replicate the previously cited studies, instead, focusing on the relationship-fit between students and their supervisors. As illustrated above the relationship between students and supervisors can enable or hinder student progress and forms an important aspect of the student's academic journey. In addition, there is a clear need for more studies that investigate supervision from a quantitative perspective. Thus, justifying the focus on only the supervision relationship-fit in master's and doctoral education. To facilitate this discussion, master's and doctoral training needs to be contextualised within the higher education sector. The section below provides an overview of the training models used in South Africa, which demonstrates the training conditions for master's and doctoral training and supervision. The section also includes a focused discussion on online training programmes and supervision.

2.5. Training models in South Africa

According to Mouton (2011), doctoral training approaches within South Africa can be considered as either so-called 'thin' or 'thick' models (Figure 6). The thin training model refers to the typical training approach adopted between the 1980s and 1990s, where the training seemed lax compared to more modern approaches (Mouton, 2011). Student enrolment screening was informal, where no coursework for doctoral education was needed, and publication from the research was optional (Mouton, 2011). A critique of this approach was that it lacked structure, specifically from supervisors (Mouton, 2011).

Figure 6: Thick vs thin training models

Source: Author (Visme)

The thick training model, on the other hand, described by Mouton (2011), took a more robust, structured approach. Institutions or departments that utilise the thick training models include coursework in qualification programmes that expand on students' knowledge of research, which may also be a formal assessment component of the qualifications (Mouton, 2011). Proposals also undergo more rigorous screening and need to adhere to departmental guidelines in order for students to proceed with their research (Mouton, 2011). Mouton (2011) indicates that supervision within this approach is also more directive, to ensure that students conform to requirements within the timeframe of their institutions. Publication shifted from an optional extra to a stronger push for knowledge production and, in some cases, a qualification requirement (Mouton, 2011). Although there seems to be an increased shift towards using the thick model, it is not always clear which approach is dominant.

Overall, learning takes place through a more scaffolded approach in the thick model compared to the thin approach (Carter & Kumar, 2017; Kumar et al., 2020; Kumar & Johnson, 2017, 2019). As students progress through lower learning stages, they may receive less structure (moving from coursework components and the screening of proposals to more independent research activities) and less support (as funding becomes secure, and students fall into a work routine, or as they start to manage their stress more effectively) in order to ultimately graduate. Kiley (2009) refers to this process of becoming more self-reliant as 'crossing conceptual thresholds', where students tend to overcome experiences of 'stuckness', which in turn changes their thinking or approach as they grow toward more independent researchers. This was demonstrated through the research conducted by Gunnarsson et al. (2013). They found that students become more confident in their learning, to the point where disagreements with their supervisors indicate that they have achieved the level of maturity necessary for self-directed research. A sentiment shared in Carter and Kumar's (2017) article titled "Ignoring me is part of learning […]". Higher self-regulation was also related to shorter dissertation completion times (Kelley & Salisbury-Glennon, 2016). This should not suggest that students go through such processes alone, but instead, that they develop and overcome challenges as they are supported throughout their academic journeys (Anderson et al., 2006; Kiley, 2009).

Although the purpose of doctoral education is for graduates to add to the ‘knowledge economy’ (Cloete et al., 2015), the focus on publications, as Mouton (2011) also pointed out, likely has a financial incentive, due to governmental subsidy. The thick training model thus seemed to signal a shift in the South African HE sector, towards more managerial and directional training in terms of the structure that was formed (Mouton, 2011). A critique against the push for shorter completion times in favour of efficiency was discussed earlier in this chapter (see section 2.3.).

Student supervision adds to the workload of supervisors (Bøgelund, 2015; Connell, 1985; Cornelius & Nicol, 2016; Grossman & Crowther, 2015), notably if the teaching workload of supervisors is not reduced to some extent (Kumar & Johnson, 2019). Furthermore, it would appear that South African supervisors may be required to take on more administrative work when compared to supervisors elsewhere (Grossman & Crowther, 2015). This workload is further impacted by the increased structure within the qualifications, as the additional teaching component and responsibility for students’ work also impact supervisor workloads (Bøgelund, 2015).

Such increased structure thus seems to limit the autonomy of supervisors, whether in selecting possible students, or increasing pressure to produce graduates (Fourie, 2016; Mouton et al., 2015). As Connell (1985) pointed out more than three decades ago, and by researchers more recently (Bastalich, 2017; Pearson & Kayrooz, 2004), the responsibility for a student’s educational performance cannot only be placed on the supervisor. Students themselves need to take responsibility for their work progress (Anderson et al., 2006; Duke & Denicolo, 2017; Kelley & Salisbury-Glennon, 2016; Lessing & Schulze, 2004; Orellana et al., 2016). As succinctly argued by Connell: “Ultimately it is the student’s responsibility, and at a certain point, the supervisor has to let go - hard as that may be” (1985, p. 41). More recently, such responsibility also requires wider stakeholder involvement (within the stated example, this included governmental and institutional responsibilities) (Bastalich, 2017). Similarly, student departments may affect their educational journeys, more so than their institutions, through the policies implemented (Golde, 2005) or the learning environments provided (Herrmann & Wichmann-Hansen, 2017). Master’s and doctoral training abroad has also started to receive more support and guidance from multiple sources within the institution. However, such support is accompanied by expanded supervision responsibilities and increased institutional oversight (Hasgall et al., 2019).

For online educational programmes, it furthermore should be considered that students are typically not located on or near the university campus, and might conduct their studies outside the geographical boundaries of South Africa (Manyike, 2017; Nasiri & Mafakheri, 2015). Although similarities are shared in the supervision processes of on-campus and online students, online supervision has several limitations in terms of contact with students (e.g. formal or informal meetings) (Kumar et al., 2020). Sverdlik et al. (2018) excluded online programmes from their article, arguing that students who study online (at a distance) have different experiences of their study environment. Students typically access their learning material online, and communicate with their supervisors or other university stakeholders electronically, whereas face-to-face meetings may be rare and infrequent, if they occur at all (Cornelius & Nicol, 2016; Mouton et al., 2015). As opposed to situations where students live close to campus, face-to-face meetings may be held at least once a month (Mouton et al., 2015). The lack of in-person meetings can easily result in misunderstandings, and may increase the difficulty of student supervision (Cekiso et al., 2019; Kumar & Johnson, 2017). Students studying at a distance might become over-reliant on their supervisors, since they have fewer opportunities to interact with peers or other researchers (Nasiri & Mafakheri, 2015). In addition, students may feel they are receiving insufficient feedback if they are not able to interact with their supervisors (Cekiso et al., 2019). On the other hand, findings by Lessing and Schulze (2004) suggest that experienced supervisors do not see a problem with supervising within a distance education context. At the same time, not all students identify any particular issues with this supervision model (Andrew, 2012). Nonetheless, online learning situations may exacerbate students' sense of loneliness (Andrew, 2012; Kumar et al., 2020; Owler, 2010). Supervisors become the contact point for their students, and thus form their main point of reference, instead of their institutions or departments (Gray & Crosta, 2018; Nasiri & Mafakheri, 2015), highlighting the importance of supervision practices within master's and doctoral training.

The benefits of online supervision were listed in the online supervision guide by Kumar et al. (2020). Online supervision increases access to master's and doctoral education for students who may not otherwise have been able to continue their studies. As part of this improved access, the diversity of the student population is increased, facilitating the development of new ideas, and providing education for students from minority groups (Kumar et al., 2020). Online supervision broadens the ability of qualified academic staff to supervise students from anywhere, which was previously limited by the need to physically travel to different institutions (Kumar et al., 2020).

The limitations of online education emphasise the usage of communication technology to connect with students and to connect them (Andrew, 2012; Kumar & Johnson, 2017, 2019; Maor & Currie, 2017). Kumar and Johnson (2017, 2019) found that supervisors could better support their students by creating group meetings and utilising various communication technologies to facilitate these meetings online. The formation of such groups may assist students in building their confidence during their studies, and may help ease feelings of isolation (Schulze, 2011). However, students (particularly within the South African context) do not necessarily have online access, or the study space required to participate in such online discussions (Cekiso et al., 2019), which may hinder the benefits of such technological interventions.

During the 2020 academic year, institutions globally were forced to switch to online and distance teaching due to restrictions and safety measures put in place to prevent the spread of COVID-19, which continued throughout 2021. As a result, institutions and students needed to explore new ways of connecting and continuing with their work, which may have permanently changed future supervision interactions. Where institutions were forced to take on online teaching methods, approaches that improved performance would likely persist beyond the COVID-19 restrictions.

The training models presented above outline the educational contexts that are provided or supported by institutions. Institutions may use a range of approaches to contextualise the learning of students which may relate to either the thin or thick models described above. However, in either model master's or doctoral students are supervised by a dedicated academic staff member(s). To understand supervision relationships, it is however necessary to describe the possible supervision models which may form the foundation of student-supervisor interactions. These are introduced below.

2.6. Supervision models

Supervision is viewed as a critical factor in the success of master's and doctoral students, particularly in doctoral studies (ASSAf, 2010; Fourie, 2016; Greene, 2015; Grover & Malhotra, 2003; Gunnarsson et al., 2013; Hasgall et al., 2019; Lovitts, 2008; Manyike, 2017; Marshall et al., 2017; Mouton et al., 2015; Schulze, 2011; Sowell et al., 2015; Van Lill, 2019). In doctoral education, and to some extent in master's studies, students must display independence (Council on Higher Education, 2013b; SAQA, 2012). However, students may at first require additional support to develop as independent researchers, due to the unstructured nature of master's and doctoral research (Anderson et al., 2006; Connell, 1985; Sverdlik et al., 2018). Although disciplinary differences in how supervision is conducted have been found (Mouton et al., 2015; Wichmann-Hansen & Herrmann, 2017), as well as in the activities that are prioritised (Halse & Malfroy, 2010), supervisors roles within master's and doctoral education nonetheless requires that they guide, support, and monitor their students' progress (which arguably presents similar characteristics across disciplines) (Connell, 1985; Sverdlik et al., 2018). As such, supervision can be considered a skill shared across various disciplines (Anderson et al., 2006; Halse & Malfroy, 2010; Lovitts, 2008; Vilkinas, 2002) and is referred to by Connell and Manathunga (2012, p. 6), and Andriopoulou and Prowse (2020) as essentially 'a human relationship'.

Masters' and doctoral supervision can be classified into several distinct models. The classifications that will be discussed briefly below include individual supervision (one-on-one relationships), co-supervision or team supervision (a single student receiving supervision from more than one supervisor), and group supervision (a group of students being mentored by one or more supervisors simultaneously). Supervision models are not necessarily fixed, and may transform throughout students' educational journeys.

Individual supervision, typically referred to as the 'traditional model', 'apprenticeship model', or 'single supervision', occurs when a one-on-one relationship is formed between a student and a supervisor (Figure 7) (ASSAf, 2010; Agné & Mörkenstam, 2018; Hasgall et al., 2019), and is the most prevalent model in South Africa (ASSAf, 2010; Cross & Backhouse, 2014; Mouton et al., 2015), as well as in Europe (Agné & Mörkenstam, 2018; Hasgall et al., 2019). Supervisors take on the responsibility for training and guidance. However, at times, this may be supplemented by additional support programmes in a more informal context (ASSAf, 2010). Irrespective of the increased independence of students, the supervision relationship remains a central point of contact for many students in the apprenticeship model for master's and doctoral supervision (Pifer & Baker, 2016). Such models have been critiqued because they lack the scope of collaboration needed to strengthen research projects (McKenna, 2017). As well as that the model only serves a minority of the students, and depends heavily on the availability of enough qualified supervisors to sustain such one-on-one relationships (ASSAf, 2010).

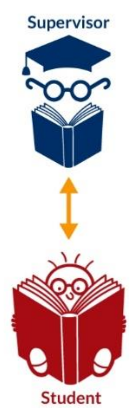


Figure 7: Individual supervision

Source: Author (Visme)

Co-supervision and team supervision typically include more academic staff members. In the case of co-supervision, two staff members are involved, where one supervisor is considered the primary contact point, and includes a second supervisor, typically for the additional experience or technical knowledge regarding student projects (Grossman & Crowther, 2015). Co-supervision approaches include added value, as a possible training ground for novice supervisors when paired with more experienced academics (Grossman & Crowther, 2015; Olmos-López & Sunderland, 2017), and may keep supervisors accountable as a result of mutual-surveillance (Olmos-López & Sunderland, 2017). In team supervision, more than two supervisors may be involved and typically form a panel (Figure 8) (Agné & Mörkenstam, 2018; Grossman & Crowther, 2015; Hasgall et al., 2019; Spaulding & Rockinson-Szapkiw, 2012). This form of supervision is almost equally as prevalent when compared to the traditional model in Europe, and is the preferred method of supervision in some institutions in New Zealand (Spronken-Smith et al., 2018). It may include staff across different disciplines (Grossman & Crowther, 2015) or institutions (Hasgall et al., 2019).

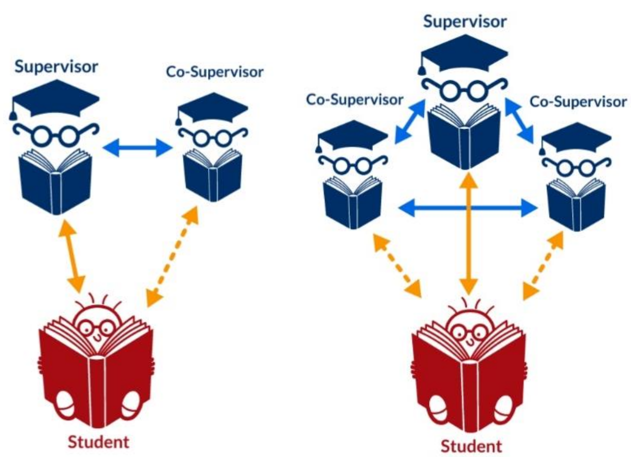


Figure 8: Co-supervision and team supervision

Source: Author (Visme)

Due to the input provided by multiple supervisors, students gain insight from multiple perspectives. An added level of complexity is nonetheless introduced where multiple supervisors are involved. This complexity results from students and supervisors needing to manage multiple supervision relationships (Gunnarsson et al., 2013; Olmos-López & Sunderland, 2017). The findings presented by Spaulding and Rockinson-Szapkiw (2012) indicate that it is also crucial for supervision team members (and by extension, co-supervisors) to work well together to ensure that students do not experience delays.

Although the responsibility for managing these multiple relationships often falls to the students, who may need to mediate between different supervisors for their work to progress (Gunnarsson et al., 2013). Student progress may be slowed through needing to wait for additional feedback, or the availability of their supervisors for meetings. After which students would likely need to spend additional time integrating feedback from multiple sources, where contradictions between supervisors may take longer to clear up (Lessing & Schulze, 2004). Furthermore, there are two potential problems that seem to accompany such an approach (in particular with co-supervision). The first relates to the division of work, where one of the supervisors may not contribute sufficient input but is credited for the work (Grossman & Crowther, 2015; Olmos-López & Sunderland, 2017), with the result that the supervision workload during co-supervision is more than the formal arrangement implies (Olmos-López & Sunderland, 2017). The second is that academic staff seem to struggle to gain advancement or promotion based only on the merits of co-supervision, possibly acting as a deterrent for academic staff to employ this model (Grossman & Crowther, 2015).

Through addressing some of the limitations of the traditional and co-supervision approaches, **group supervision** models have started to become more prevalent, where one or more of the supervisors would simultaneously supervise several students who conduct their research independently on a similar topic or area (Agné & Mörkenstam, 2018; Khosa et al., 2019). Supervisors (or in some cases departments) can also create such groups, by scheduling meeting times between their students and leading group discussions on their study progress (Kumar & Johnson, 2017). One manifestation of group supervision is 'cohort' supervision, where the students are admitted to the same programme in the same year (Figure 9) and can progress together through the research process (Agné & Mörkenstam, 2018; McKenna, 2017). This method of supervision is intended to enhance student learning from peers, provide additional knowledge sources for them to utilise in their learning process, assist in their integration into the institutional culture (Agné & Mörkenstam, 2018; McKenna, 2017; Spaulding & Rockinson-Szapkiw, 2012), and assist in placing students with suitable supervisors at the appropriate time (Agné & Mörkenstam, 2018). Evidence also suggests that group supervision methods may lead to shorter completion times than in traditional training models (Agné &

Mörkenstam, 2018), although more research is needed to corroborate these findings. However, two limitations noted in the literature around group supervision involved students possibly plagiarising each other's ideas, and limiting students' research autonomy to create more homogeneous groups (Khosa et al., 2019).

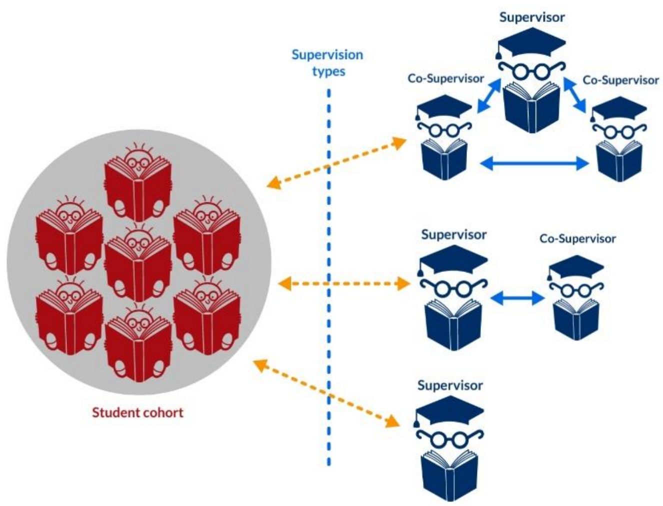


Figure 9: Group supervision

Source: Author (Visme)

The different supervision models carry certain advantages in terms of the variety of support or attention students can gain. Disadvantages likewise accompany each in terms of required resources or available expertise. However, one commonality is that students typically have a specific supervisor as a contact point (Grossman & Crowther, 2015; Grover & Malhotra, 2003; Kumar & Johnson, 2017; Olmos-López & Sunderland, 2017), although in co-supervision and team supervision scenarios, the primary roles may be negotiated between supervisors, outside of what has been formally allocated (Olmos-López & Sunderland, 2017). As Hasgall et al. (2019) argue, the role played by supervisors is not diminished as a result of increased institutional support or regulations. In Europe, supervisors increasingly work in teams, although one supervisor continues to be the focal point for master's and doctoral education (Hasgall et al., 2019). The particular supervision model employed will nonetheless impact student’s experiences, and satisfaction with their supervisory support (Pyhältö et al., 2015).

2.7. Chapter summary

This chapter presented an overview of master’s and doctoral education as a basis for the arguments made within the current study. The chapter started with a brief distinction between master’s and doctoral education, highlighting similarities and differences. The distinction between these qualifications focuses primarily on what is considered novel in doctoral research, but requires similar engagement with the research process. There is an additional similarity in the funding for both qualifications, and thus an overall push towards similar conceptualisations of student success. This comparison implies that supervision would be similar for master’s and doctoral education, where the distinction would likely stem from the complexity, depth, or scope of the research project.

The view of student success adopted for this study considered how long students take to complete their studies, which is personified within arguments for higher education efficiency, and consistent with the Socio-critical model adopted by Unisa (Subotzky & Prinsloo, 2011). However, it is recognised that such a view of success may be unsustainable if the higher education sector does not allow students (and their supervisors) enough time to produce high-quality research. On the one hand, the quality of students’ work might suffer if they are essentially penalised for taking too long (according to industry standards) (Torka, 2020; Wingfield, 2011), but on the other hand, the system needs to ensure efficiency in order to remain sustainable (Torka, 2020).

According to higher education research, students take several years to complete their master’s and doctoral studies, typically several years longer than the minimum time. Several factors were discussed which may influence whether or not students complete their studies, and how long their qualifications may take for those who do. One of the important influences recognised in the literature was student supervision.

The chapter describes the training models used within the South African context, in addition to an overview of supervision models, which provide distinct educational contexts with various benefits and limitations for each. These supervision models thus necessarily link back to the initial description of master's and doctoral education at the beginning of this chapter, where each supervision model may be adopted in the various qualification types. Although students typically complete a dissertation or thesis, the completion of doctoral qualifications by publication is also possible (ASSAf, 2010), as well as increasing in South Africa (Mouton et al., 2015). Where students are enrolled in professional qualifications with formally structured curricula, their supervision mode would be incorporated into the research component of their qualifications. Students may thus form part of a cohort within a qualification, follow the same structured programme, and fall within one of the supervision models for their research (ASSAf, 2010).

The following chapter contextualises master's and doctoral supervision further within theoretical perspectives of the teaching approach. Supervision relationships are considered at a conceptual level. This provides a theoretical foundation for the current project and, in particular, a way to operationalise supervision relationships.

Chapter 3: Supervisory relationships

This chapter provides a theoretical lens through which to view the supervision relationships between students and their primary supervisors. Theoretical frameworks in HEI act to predict student success and guide student support initiatives. Student supervision is intrinsically linked to HEI, which provides a context for the supervision and students' learning to take place. It is therefore important to understand the Unisa socio-critical model introduced in the first chapter, which frames student supervision within the institution. However, given that the socio-critical model does not explicitly focus on master's and doctoral education, other theoretical frameworks are explored that are more suited to this study. Several theoretical frameworks related to master's and doctoral supervision are compared and critiqued to accomplish this purpose. Comparisons include multiple perspectives to ensure the research instruments are developed from a sound theoretical foundation (De Vos et al., 2011).

This chapter thus begins by contextualising this project within the Unisa socio-critical model that provides a "framework for understanding, predicting, and enhancing student success" within the University of South Africa (Subotzky & Prinsloo, 2011, p. 177). Such a contextualisation would ensure that the measurements of supervision relationships within this study do not fall outside the praxis of the institution. This contextualisation is followed by a discussion of theoretical perspectives of master's and doctoral supervision. Two types of theoretical frameworks, fit theory (Baker & Pifer, 2015) and contingency theories of supervision (Boehe, 2016; Gatfield, 2005) are explored and integrated in this chapter to assist in understanding supervision relationships. Fit theory as used in this thesis, explains that students and supervisors would be more likely to be successful if they experience greater congruence (fit) in their supervision relationship. However, fit theory does not explain how to operationalise this relationship to measure congruence, requiring an additional theoretical framework. According to Gatfield's (2005) contingency theory of supervision, supervision relationships are classified within one of four supervision styles. Each supervision style is defined by how structured or supportive the relationships are (Fourie, 2016; Gatfield, 2005; Johansson & Yerrabati, 2017). The integration of these two theories is undertaken to understand whether congruence (fit Theory) within the relationships between master's and doctoral students and their supervisors (contingency theories) may influence time to completion in a higher education, ODeL context.

3.1. Theoretical contextualisation

The socio-critical model, which was introduced in the first chapter, mainly focuses on the support and development of undergraduate students and does not provide a focused examination of the interaction between staff members (as supervisors) and master's and doctoral students (Subotzky & Prinsloo, 2011). Undergraduate students have shorter course times, structured assignments, and examination blocks. The research component for master's and doctoral students is designed to be more fluid, with fewer formalised compulsory contact points throughout the academic year and academic journey. In addition, the contact points for master's and doctoral students are not necessarily designed to monitor progress or achievement by the institution. For example, annual registration acts as an administrative contact point, where the institution gains more information about the students (Ampaw & Jaeger, 2012; Subotzky & Prinsloo, 2011). Contact points are primarily facilitated via the supervisory relationship. These are not necessarily reported on in detail to the institution.

The relationship between students and their supervisors has been cited to be an integral aspect of students' success by multiple authors (Fourie, 2016; Gray & Crosta, 2018; Grover & Malhotra, 2003; Manyike, 2017; Pifer & Baker, 2016; Sowell et al., 2015; Van Lill, 2019). Thus, when considering that students' contact with the institution is typically formalised through their relationships with their supervisors (Gray & Crosta, 2018), this would imply that the nature of these relationships would strongly influence their academic journey and, by implication, their time to completion. For this reason, it becomes critical to investigate this phenomenon through the theoretical lens of a framework specialising in describing supervision relationships. As suggested by Subotzky and Prinsloo (2011), sustained success may only be achieved if one considers the fit between the student and the institution (supervisor). Consistent with the research focus, fit theory is expanded on below, followed by formalised theories regarding supervision relationships.

3.2. Fit Theory

Theoretical frameworks for master's and doctoral supervision, such as fit theory, have increasingly borrowed from organisational literature (Baker & Pifer, 2015). This assists in leveraging knowledge generated in a seemingly separate field of study to better understand master's and doctoral supervision (Vilkinas, 2002). Equating master's and doctoral education with organisational profiles, at face value, seems consistent when considering the increased independence required of students in their roles at higher qualification levels (Vilkinas, 2002; Ward & Brennan, 2018). Furthermore, the issue of student fit is integral to Subotzky and Prinsloo's (2011) understanding of student success[27].

'Fit theory' posits a need for congruence between individual and organisational values (Baker & Pifer, 2015; Edwards & Billsberry, 2010; Wheeler et al., 2005). This congruence would appear to predict commitment, intention to leave, and satisfaction in organisational research (Edwards & Billsberry, 2010; Su et al., 2015). Within master's and doctoral supervision, the perceived fit or misfit of their study environments (Golde, 2005) or the predominant supervisory styles (Bastalich, 2017; Johansson & Yerrabati, 2017; Woolderink et al., 2015) may influence the ability of students to complete their degrees (Golde, 2005; Johansson & Yerrabati, 2017; Pyhältö et al., 2015). Therefore, it is crucial to investigate how matched relationships may influence student success (Sverdlik et al., 2018).

Ward and Brennan (2018) describe that at a higher level of abstraction, fit theory can become complex. Jansen and Kristof-Brown (2006) describe fit theory as multidimensional, implying that different factors may simultaneously influence students and their supervisors. Baker and Pifer (2015, p. 308) describe fit as a fluid concept that is: "influenced by the context, individual characteristics and relationships", conceptualising fit as constantly changing. Thus, the student-supervisor fit may be viewed

[27] It is important to note that the idea of student fit has formed part of student success research for several decades. The seminal work of Tinto (1975), who cited Spady's 1970 and Durkheim's Theory of Suicide, as well as subsequent theoretical development, were initially concerned partly with student integration in higher education. Within this thesis, such theories were not considered given their focus on undergraduate students, however, remain an important foundation for higher education, as well as Subotzky and Prinsloo's (2011) understanding of student success discussed later.

as a dynamic process, which can be influenced by various factors throughout students' educational journeys.

Focusing on doctoral education, Baker and Pifer (2015) highlight three theoretical constructs of fit theory that may be transferable from organisational studies to master's and doctoral research in higher education, namely: person-culture fit, person-vocation fit, and person-environment fit. Although the main focus of the approach by Baker and Pifer (2015) is on preparing doctoral graduates for employment within both academic and non-academic contexts, doctoral student success is included within their framework. The three conceptualisations discussed by Baker and Pifer (2015) posit several outcome factors for students.

Person-culture fit considers the congruence between the shared value systems of students and their academic departments, disciplines, or related professional associations. Outcomes include that graduates remain active in academic spheres, obtain successful job placements, student identity formation around their expertise, or become accepted within a research community (Baker & Pifer, 2015). Ward and Brennan (2018) have expanded on this conceptualisation to include student difficulties in transitioning to their roles in doctoral education as a divergence in person-culture (student-doctoral culture) fit.

Person-vocation fit relates to student identity formation around intended careers, goals, or interests (Baker & Pifer, 2015). Traditionally, doctoral graduates pursue related academic careers upon completion of their degree. Recently, this trend has shifted to include a greater variety of career options (Baker & Pifer, 2015; Roach & Sauermann, 2017; Ward & Brennan, 2018). According to Baker and Pifer (2015), this shift may require an investigation into the preparedness of doctoral graduates within these new career roles. In addition, this shift in career focus may diminish doctoral students' motivation for completing degrees that include such "stringent quality and critical-feedback mechanism" (Ward & Brennan, 2018, p. 4), which are more consistent with careers in the academic context. As a result, Baker and Pifer (2015) argue for including experiences related to future professional positions during the degree programmes to increase the doctoral student understanding, and facilitate person-vocation fit.

Person-environment fit refers to the congruence between students and their environment and relationships that relate to their academic journey, which include: “academic departments, institution, region, faculty members, and fellow students” (Baker & Pifer, 2015, p. 299). One of the aspects included within the person-environment fit is the supervision relationship (Baker & Pifer, 2015). Students typically have an ideal image of what supervisors ought to be (Ali et al., 2016; Davis, 2020; Deuchar, 2008; Holbrook et al., 2014). A shared understanding of the supervision relationship between students and supervisors cannot however be assumed (Al-Muallem et al., 2016; Fleming et al., 2013; Orellana et al., 2016; Pearson & Brew, 2002; Pyhältö et al., 2015), where ensuring that students and supervisors are aware of each other’s expectations seems to be related to student satisfaction and risk of attrition (Pyhältö et al., 2015). Increased perceived fit was related to student satisfaction and the way in which students experienced support from their supervisors (Pyhältö et al., 2015). Furthermore, perceived divergence in the person-environment fit, or ‘misfit’, may affect student persistence to graduation (Baker & Pifer, 2015; Pyhältö et al., 2015). Ward and Brennan (2018) include the private environments of students, such as work or home contexts, within this conceptualisation, arguing that the lines between educational contexts and other aspects of students’ lives become blurred at the master’s and doctoral levels of study. In terms of relationships, Ward and Brennan (2018) included support from family and friends and supervisors (Figure 10).

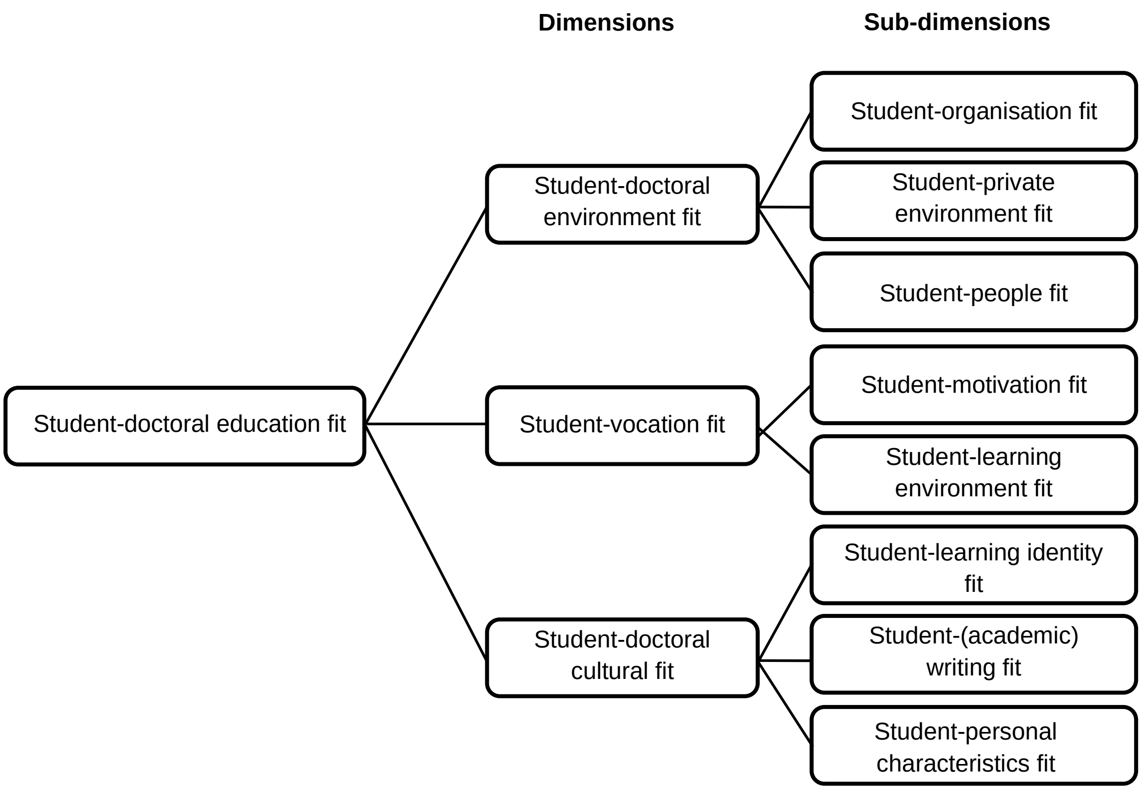


Figure 10: Student-doctoral education fit framework (Ward & Brennan, 2018, p. 4)

The expansion by Ward and Brennan (2018) resulted from their perception that Baker and Pifer (2015) only considered the learning curriculum or 'doctoral fit' (Ward & Brennan, 2018). The educational, private, and professional contexts of students' lives are often intertwined within more advanced degree programmes. This may be particularly true for non-traditional students, who often work or study from home and are required to balance additional responsibilities in their lives. Organisational factors, or other aspects of the students' lives, are seen as part of their situatedness as defined by Subotzky and Prinsloo (2011), that form the pre-existing context of the relationship. However, following the approach by Boehe (2016), this study will exclusively focus on supervision relationships.

Retaining the focus of this project only on the supervision relationship is not meant to imply that students' private or professional lives do not affect their academic journeys. These aspects, however, lie outside of the scope of this thesis. This approach, rather, follows from the literature in which the importance of the supervision relationship has been reiterated.

Congruence between students and supervisors (increase in student-supervisor fit) strengthens their academic relationships (Connell, 1985; Pifer & Baker, 2016; Seagram et al., 1998; Sowell et al., 2015; Spaulding & Rockinson-Szapkiw, 2012), and misfit may increase student self-doubt (Pifer & Baker, 2016), feelings of isolation or neglect (Castelló et al., 2017; Holbrook et al., 2014), or arguably lead students to further delays or withdrawal (Connell & Manathunga, 2012). However, given the complexities of master's and doctoral supervision (Fourie, 2015; Gray & Crosta, 2018), as well as that it is important for students to perceive the support that was provided (Greene, 2015), it is unlikely that perceived misfit would automatically lead to withdrawal, or increased time to completion, as the only available alternatives (Wheeler et al., 2005).

3.2.1. Misfit

Perceived misfit within students' academic journeys may lead to psychological distress or become a source of conflict within supervision relationships (Al-Muallem et al., 2016; Cornelius & Nicol, 2016; Phillips & Pugh, 2005; Su et al., 2015; Wheeler et al., 2005). However, relationships that start with a perceived misfit may later become a valuable support system for students (Sverdlik et al., 2018).

Continuing to draw on organisational theories of fit, Wheeler et al. (2005) indicate that there would essentially be five different options available to individuals (in this study to students or supervisors) to deal with a perceived misfit. The five options, in order, include: adaption; exit; impression management; voice; and in-action (Wheeler et al., 2005). Students and supervisors may evaluate perceived fit or misfit at various intervals during the academic journey. However, such an evaluation is more likely to occur during the initial formation of the relationship, or when an unplanned event occurs (Wheeler et al., 2005). Thus, initial impressions of supervision relationship fit may endure, unless an evaluative process is triggered.

When misfit is perceived, the student or supervisor must determine whether they are willing to **adapt** to their environment. If it is possible to adapt, they need to change some aspect of their beliefs or values in order to experience increased fit (González-Ocampo & Castelló, 2019; Wheeler et al., 2005). However, if they are neither able nor willing to adapt, this would require further options to be explored (Wheeler et al., 2005). Adapting to every situation may not be possible or desirable (Wheeler et al., 2005), since each context and relationship is unique.

Where adaptation is not possible, the next consideration is **exit** (Wheeler et al., 2005) by discontinuing the relationship, or for students to drop out. Students can voluntarily deregister, or decide not to reregister for their studies. Alternatively, either the student or supervisor can request that their relationship discontinue. Voluntarily or involuntarily discontinuing the relationship for students may result in dropping out of HEI, changing supervisors, or changing to another institution. Voluntary discontinuation may not be an option for every student, due to external pressures, or poor outside alternatives (Wheeler et al., 2005), which may hinder a student's ability to leave a specific organisation or supervisor. The political nature of higher education institutions globally as well as within South Africa, combined with the social pressure attached to completing a degree from a particular institution, may result in students feeling unable to drop out of their studies. Completing a master's or doctoral degree, or associating with a particular institution, may act as formalised or informal entrance requirements to certain employment opportunities.

Students or supervisors who experience a mismatch, who may be unable to adapt or exit the relationship, may begin to implement **impression management** strategies. Such a strategy would aim to protect their identities and self-conceptions, while projecting the desired behaviours within their educational contexts (Wheeler et al., 2005).

Students, or supervisors, may also decide to **voice** their concerns or dissatisfaction. Voicing their concerns may be done through general protest or direct communication (Wheeler et al., 2005) within their departments or faculties. It should be noted that supervisors would be in a position of power in this type of situation, as they are typically the primary contact point for students, who may not be aware of where to search for assistance.

Finally, students or supervisors may choose to do nothing, referred to as **in-action** (Wheeler et al., 2005). Essentially the approach, to 'grin and bear it', may result in increased frustration, and students who slowly disengage during their studies. Some students may continue their studies, determined to complete their degrees, essentially completing a 'do-it-yourself' master's or doctorate. However, this approach is also detrimental (Wheeler et al., 2005), as it is likely to increase the completion time, or the chance of dropout, if students cannot hold out long enough.

However, Holbrook et al. (2014) argue that not all forms of misfit are necessarily negative. Their (ibid.) study suggests that when expectations of students or supervisors are exceeded, a mismatch occurs between the interaction experience, compared to a lower previous expectation. This suggests that the way in which students or supervisors respond to instances where a lack of fit is presented is unique to each individual (Holbrook et al., 2014).

It should be made explicit that the current study was not aimed at determining behaviours resulting from a perceived misfit. The above discussion brings to light the importance of fit within the context of master's and doctoral supervision in higher education. However, it is crucial to be aware that supervisory relationships are complex, and do not result in simplistic outcomes, regardless of whether fit or misfit is experienced. Such relationships are inherently unpredictable and non-deterministic (Sowell et al., 2015, p. 54). Investigating student actions that result from a perceived misfit would be better suited for research beyond the present thesis, and may form a natural second step after the current study.

Due to the nature of master's and doctoral studies, students and supervisors must work closely together (ASSAf, 2010), suggesting that the tone of their relationship could influence their performance throughout their academic journeys. The importance of the supervisory relationship has been reiterated in studies which found that perceived congruence between students and supervisors (increase in student-supervisor fit) strengthens their academic relationships. Stronger supervision relationships may, in turn, influence student persistence, and lower the likelihood of student withdrawal (Baker & Pifer, 2015), or may affect students' time to completion (Murphy, 2009; Ward & Brennan, 2018). Although the way in which students and supervisors perceive supervision activities are not yet well understood (Pyhältö et al., 2015) nor fully conceptualised in the theoretical framework of fit. This requires adding a framework that describes what should happen in the supervisory relationships.

3.3. Supervision theories

Master's and doctoral supervision is a complex academic and interpersonal skill (Al-Muallem et al., 2016; Connell & Manathunga, 2012; Fourie, 2016, 2015; Gray & Crosta, 2018; Sambrook et al., 2008). It comprises of a variety of interrelated facets (Halse & Malfroy, 2010), which are seemingly not well understood (Alam et al., 2013; Fourie, 2016, 2015). There are various views on supervision styles or roles that supervisors ought to adopt (Deuchar, 2008; Harwood & Petrić, 2020). Without a definitive model of supervision (Gray & Crosta, 2018), these views seem to translate into a growing list of skills, functions, or requirements that constitute what it means to be a successful supervisor (Deuchar, 2008; Gray & Crosta, 2018; Jones, 2013; Lee, 2008). In the absence of a single model of supervision, several attempts have been made to understand master's and doctoral supervision, typically by aggregating the lists of tasks into more abstract thematic areas, to classify supervision preferences or approaches, commonly referred to as supervision style, roles (Lee, 2007; Pearson & Kayrooz, 2004; Wichmann-Hansen & Herrmann, 2017), or metaphors (Durette et al., 2016).

In defining supervision styles, Harwood and Petrić (2020) argue that, when asked, supervisors would likely not merely reduce their supervision approaches into a neat classification, but would instead define their supervision models in terms of their experiences. However, predefined categories of different supervision models carry certain advantages, primarily in terms of the feasibility of gaining evidence on supervision practices (Harwood & Petrić, 2020). Predefined theoretical frameworks have the additional advantage of including a layer of abstraction, through the aggregation of the list of tasks to create more explanatory models, which may allow for comparisons (Healy, 2017) across supervisors and supervision contexts.

Pearson and Kayrooz (2004) nonetheless describe a delicate balance between a theory providing an appropriate amount of abstraction and claim to explanatory power, and a view that each supervision relationship is so unique that generic descriptions cannot be applied. The first instance has the potential to hold supervisors responsible for everything. It may result in the rigid adoption of best practice guidelines which Pearson and Kayrooz (2004) describe as the 'Atlas complex'. The other extreme posits that it would not be possible to reduce supervision to a theoretical framework (Pearson & Kayrooz, 2004).

Different authors (Boehe, 2016; De Kleijn et al., 2012; Gatfield, 2005) have their own versions of defining supervision styles, sometimes using adapted or overlapping attributes. As a result of such differences or similarities, comparisons between frameworks may be complicated. Operationalisations are often implicit, and not typically tested through quantitative measurements (Wichmann-Hansen & Herrmann, 2017). Nonetheless, there is some overlap between approaches, presumably since these draw on similar literature sources, or provide possible evidence supporting the core principles of such frameworks.

The thematic classification of supervision models seem to fall within two broad classification systems. The first method of classification considers the concept of supervision beliefs, or orientations of supervisors, to distinguish between several roles or models of supervision, mainly from the perspective of supervisors (Lee, 2008; Murphy et al., 2007; Wichmann-Hansen & Herrmann, 2017). Within this classification system, supervisors may use multiple supervision models to inform their approach (Lee, 2008), as the models are not mutually exclusive (Lee, 2007). This approach seems to be positioned as product-focused, where the emphasis is placed on the type of graduates produced. The second classification system borrows from organisational theories, and combines the set supervision tasks into independent thematic areas, or overarching factors. These factors can be measured into distinctive supervision styles or relationships (Boehe, 2016; Gatfield, 2005; Wichmann-Hansen & Herrmann, 2017). Supervisors may adapt their approach over time, or between students, as their contexts require, although each relationship can only be classified within a single model at any given time (Boehe, 2016; Gatfield, 2005). These theories seem to be task-focused in their approaches, which depend on the context of each relationship (contingency theories).

Within both classification systems, the different supervisory roles are conceptualised into character types, which provide an explanatory function to each framework. In both instances, it seems as if the development of these systems was mainly conducted through naturalistic research methods, referring to various qualitative research approaches (Bastalich, 2017; Bøgelund, 2015; Franke & Arvidsson, 2011; Gatfield, 2005; Gray & Crosta, 2018; Johansson & Yerrabati, 2017; Lee, 2008; Murphy et al., 2007; Wichmann-Hansen & Herrmann, 2017; Wright et al., 2007). Some testing of the frameworks has been conducted. However, larger quantitative projects are less prevalent (Fourie, 2016; Pyhältö et al., 2015). Theoretical perspectives from both classification systems are discussed below, so as to provide an overview of current theories on master's and doctoral supervision.

3.3.1. Product focused theories

Supervision models that could be interpreted from the first classification model (Product focused theories) are concerned with the purpose of supervision practices (Pearson & Brew, 2002). These models focus on why supervision is conducted in a particular way, specifically on the underlying motives of supervisors. The underlying beliefs or motivations of supervisors become central within these frameworks (Åkerlind & McAlpine, 2017; Bøgelund, 2015; Lee, 2008; Murphy et al., 2007; Wright et al., 2007).

In a study to identify the supervision models used by master's and doctoral supervisors, Lee (2007) summarises several models from the literature on supervision. Lee (2008) expanded on the conceptual framework developed by Brew (2001) and Pearson and Brew (2002) to identify five separate supervision models, namely: functional, emancipation, enculturation, critical thinking, and relationship development models (Table 2).

The **functional models** of supervision refer to the roles that supervisors play as project managers, or only giving direction. This model is concerned with providing practical advice to assist students with their development (Lee, 2007, 2008) and emphasises performance. As a result, it is possible to use traditional project management tools to track student progress (Lee, 2018). Brew (2001) described this approach as a set of tasks combined to solve specific problems (Brew, 2001; Pearson & Brew, 2002). Since each task is conceptualised as distinct, the model was referred to as the domino conception, highlighting the way in which each task has a particular place within the process (Brew, 2001).

The **emancipation model** argues that students need to be progressively challenged and supported through their studies. The model draws on the conceptualisation and research around mentoring (Lee, 2007, 2008). Supervisors take an active, hands-on approach to supervisory roles as non-judgemental advisors, where students learn the most by experiencing the work themselves (Lee, 2007, 2008). The goal of the emancipatory approach is to assist the development of students, specifically to become independent scholars (Lee, 2018). This approach is linked to Brew's (2001) journey conception, where the researcher's interests and development is an important component. There is a focus on the researcher and whether or not they experience direction within their work (Brew, 2001; Pearson & Brew, 2002).

Within the **enculturation model,** supervisors act as gatekeepers to various opportunities, including learning resources or the academic discipline. Supervisors who make use of this model of supervision assume that doctoral candidates will enter academia after the completion of their studies. Thus, this model is not limited to students' learning experiences in their studies. It includes working experience within academic departments that may be necessary to take up future employment as academic staff members (Lee, 2007, 2008). This model emphasises forming part of a group and fostering a sense of belonging (Lee, 2018). Enculturation refers to the social aspect of research presented by Brew (2001), referred to as trading. Publication, social networks, and grants focus on becoming part of the disciplinary traditions of research. In addition, the approach highlights the need for some researchers to receive recognition for their work (Brew, 2001; Pearson & Brew, 2002).

The **critical thinking model** assumes the responsibility of teaching students to evaluate arguments rationally. This approach finds its basis in the Socratic method of systematically questioning in order to uncover underlying assumptions. In doing so, there are three stages to the critical thinking model (Lee, 2007, 2008), namely: “Problematising, finding connections, and uncovering conceptions” (Lee, 2008, p. 273). The emphasis within this model is to ensure intellectual rigour and analysis, where students need to learn to recognise the flaws in an argument (Lee, 2018). The critical thinking model corresponds with the layer conceptualisation presented by Brew (2001). The goal of the layer conceptualisation is to illuminate research findings, making previously unknown connections by exploring project data and making use of theoretical ideas (Brew, 2001; Pearson & Brew, 2002)

Relationship development focuses on the emotional intelligence and flexibility supervisors need to help students through their journey (Lee, 2007, 2008). This approach aims to develop a positive supervisory relationship that supports students throughout their academic journey. This does not mean that supervisors and students need to become friends, which may hinder the ability of supervisors to be critical of their work. However, dissatisfaction within this relationship has been linked to poor completion rates (Lee, 2008). Building relationships requires the ability to manage boundaries and expectations, in addition to preventing conflicts (Lee, 2018). Lee defines the core of this model as “altruistic, benevolent, and demonstrates goodwill” (2018, p. 881). This model furthermore forms part of the expansion of the work conducted by Brew, and Pearson (2002) and Brew (2001), intended to improve on previously available frameworks.

Table 2: Link between Brew and Lee

Brew (2001)	Definition	Lee (2007)
Domino conception	Views research as a set of tasks that must be combined to solve a particular problem or answer a specific question.	Functional
Layer conception	Places focus on discovering or creating meaning linked to hidden meanings.	Critical thinking
Trading conception	Views research as a product or end goal exchanged in social markets, where one gains recognition and reward.	Enculturation
Journey conception	Considers the personal journey of discovery or transformation of the researcher.	Mentoring
-	Recognises that supervision requires flexibility, as well as the need to consider the emotional aspect of student's journey.	Relationship development

Adapted from (Brew, 2001; Lee, 2007)

Although the above section describes five seemingly distinct models for master's and doctoral supervision, these are not entirely separate. Supervisors use various combinations of these models to produce different types of graduates (Lee, 2007, 2018). Lee (2008) notes that the models are not dependent on disciplines, thereby suggesting that the models apply to supervision relationships across academic departments.

Different but comparable classification approaches to master's and doctoral supervision have also been identified. Grant, Hackney, and Edgar (2014) preliminarily identified three approaches to supervision, which they present as three metaphors, namely machine, coach, and journey. These seemed to share core themes with those developed by Bøgelund (2015), namely: the academic perspective; the market perspective; and the changing society perspective.

Within the analysis of the three metaphors in Grant et al. (2014), the **machine** characterised supervisors as instruments of the institution. It requires some form of adherence to policy or procedure and provides evidence of monitoring and feedback on student progress (Grant et al., 2014). Bøgelund's (2015) market-oriented supervisor focuses on working with industries where research problems may have already been defined, and where projects take a more applied research approach. The focus is on the efficient use of resources and valuable results, where the author used the term Project Leader as a role descriptor (Bøgelund, 2015). Alternatively, the focus is placed on students’ skills development to ensure they possess the abilities required in a research-related career (Åkerlind & McAlpine, 2017). Similarities are shared with the functional approach, and to some extent with the enculturation approach suggested by Lee (2007).

The **coach** guides students throughout their thesis process, allowing them to develop as researchers. This is accomplished by advising students’ work, and avoiding acting as censors to the student’s writing (Grant et al., 2014). This role shares similarities to Bøgelund’s (2015) academically oriented supervisor, where the author used the role description of a professional sparring partner. For supervisors using this approach, value is placed on knowledge production as a critical exercise, and on the development of students into academic researchers (Bøgelund, 2015). Effectively taking the form of ideas development ultimately leads students to conduct research that adds new perspectives to the academic project (Åkerlind & McAlpine, 2017). This metaphor shares aspects of the critical thinking concept, as well as in part the mentor concept proposed by Lee (2007).

Finally, the **journey** metaphor illustrates a learning experience for both student and supervisor. This approach emphasises the supervisor’s research interests, and allows the researcher to be corrected by their students (Grant et al., 2014). Bøgelund’s (2015) changing society perspective reiterates the importance of the development of students, and includes a distinctive focus on the training of international students. Individualised student support gains more attention within this perspective, where the role descriptor here refers to an all-around facilitator (Bøgelund, 2015). Consequently, the focus is placed on students’ personal development, and supporting their learning by recognising them as individuals with their own career aspirations (Åkerlind & McAlpine, 2017). Commonalities within this metaphor are found in the mentor and relationship development concepts in the framework of Lee (2007).

Similar to the perspective proposed by Lee (2007, 2018), supervisors are not restricted to a single role. They may identify with all of these metaphors to a greater or lesser degree (Grant et al., 2014). Bøgelund (2015) takes an additional step in their framework by linking each supervision role with a core university agenda. This would refer to academically oriented supervisors focusing on quality research outputs, market-oriented supervisors focusing on the economic viability of research and research efficiency, and supervisors focusing on changing social perspectives, placing greater importance on international collaborations (Bøgelund, 2015).

The abovementioned supervision frameworks share some common features and provide some explanatory power to supervision practices. However, the overlapping attributes mean that measuring categories or character-typed personae only become practical within more naturalistic methods of investigation, and even then, may be subject to interpretation or correction. In practice, the intention of supervisors (grooming students for academic work or professional careers) should not change the measurable results of students. Both outcomes diverge, due to the practical realities of their contexts. However, time to completion, quality of work, and research methodology should ideally not become compromised due to supervisory motives.

The abovementioned classification furthermore seems to assume that students are passive, defining the relationship as centring around the supervisor. Instead of focusing on a supervisor's intentions or drives, it may be important to consider instead how they go about 'doing supervision'. The way in which master's and doctoral supervision is conducted would naturally share elements with the abovementioned frameworks. However, the different elements are organised into distinct thematic areas. Actions such as regular scheduling of meetings may be shared in the above categories, though it additionally functions to frame the relationship, regardless of the intended outcome. Fourie (2016) has argued that identifying the roles of supervisors (as described above) may be helpful in supervision discussions, or in negotiating supervisory relationships. However, this focus does not provide a foundation for discerning between specific roles and practices.

3.3.2. Task-focused theories (contingency theories)

The theories discussed in this chapter that are grouped as part of the second classification focus on contingency theories of supervision. As opposed to the product-focused theories discussed above that emphasise the type of graduate that is trained, task-focused theories are based on contingency frameworks to explain supervision styles. Similar to the theory of fit, contingency theories of student supervision provide another example of theoretical frameworks borrowed from organisational literature (Cross & Backhouse, 2014). Theories focus on clustering different elements or tasks within the supervisory relationship into independent thematic areas or overarching factors. These factors can typically be plotted on a two-axis grid, and identify four quadrants that underpin four distinct supervision styles or relationships (Boehe, 2016; Gatfield, 2005; Wichmann-Hansen & Herrmann, 2017).

A fundamental assumption of contingency theories is that no single approach will work in every situation, but that any given approach will depend on specific circumstances (Cross & Backhouse, 2014; Sambrook et al., 2008). This situational focus reiterates that students go through certain transition points throughout their academic journeys (Franke & Arvidsson, 2011; Pifer & Baker, 2016), requiring that both students and supervisors (institutions) remain adaptable so as to ensure successful outcomes, as proposed by Subotzky and Prinsloo (2011). Supervision relationships would be classified within a single model at any particular time (Boehe, 2016; Gatfield, 2005). Although these relationships presumably also change as the relationship develops (Connell, 1985; Sambrook et al., 2008), as the students progress with their studies (Anderson et al., 2006; Gunnarsson et al., 2013), and as their support needs change with time (Orellana et al., 2016; Vilkinas, 2008).

These changes are, to an extent, part of students' progress, where increasing students' autonomy can be viewed as an end in itself (Anderson et al., 2006; Sidhu et al., 2016). Nonetheless, it can be expected that supervisors, and presumably students, would have a preference for a particular style, regardless of their ability to adapt (Åkerlind & McAlpine, 2017; Ali et al., 2016; Gatfield, 2005; Lessing & Schulze, 2004; Marshall et al., 2017; Roach et al., 2019; Sinclair, 2004; Vilkinas, 2008). Supervisors have a particular understanding of supervision relationships, and may work towards developing students as researchers, whereas students may prefer to get guidance on completing their qualifications. In a study by Kandiko and Kinchin, one of the students explained: "I don't know why my supervisor keeps asking me what I am doing socially and how I am feeling. It is like she wants to be my friend – I would like her to just tell me what to do" (2012, p. 13).

Although this review of theoretical frameworks did not take a historical account of the origins of supervision theories, Murphy et al. (2007) have argued that this contingency theory pattern was evident in older studies, such as that of Fox in 1983, whereas Fourie (2016, p. 167) describes Gatfield (2005) as the author who “brought this topic to prominence”. Gatfield (2005) created a theoretical framework through an extensive literature review, clustering 80 variables on supervision into a two-axis managerial grid, credited to Blake and Moulton’s work in 1964 (Gatfield, 2005; Johansson & Yerrabati, 2017). This model was further investigated through in-depth interviews with students and supervisors (Gatfield, 2005).

Gatfield (2005) proposed that two overarching contingency factors define supervision relationships, namely: structure and support. Several authors have recognised similar dichotomous conceptual models within the literature (expanded on more below), which form the foundation of supervision relationships (De Kleijn et al., 2012; Khosa et al., 2019). These two factors are cross-tabulated to form a four-quadrant grid designating different supervisory styles (Fourie, 2016; Gatfield, 2005; Johansson & Yerrabati, 2017). A third factor entitled exogenous factors, refers to elements outside the direct supervision relationship (Gatfield, 2005).

Exogenous factors refer to those variables brought into the relationship by the student and the supervisor (Table 3), not relating to structure or support. Similar to the identity, attributes, capital, and habitus proposed by Subotzky and Prinsloo (2011), these variables are related to the student and supervisor as individuals. A multitude of factors could be argued to form part of this grouping. Gatfield (2005) highlights several factors related to the participant’s psychological profiles, including motivation, existing skills, maturity, and the personality makeup of each student. In addition to a student’s social and cultural background alongside their professional experiences (Cornelius & Nicol, 2016). Although exogenous factors may influence the supervision relationship, Gatfield (2005) did not focus specifically on exogenous factors, providing a more comprehensive discussion of the structure and support factors, and combining supervision styles in this theory.

Table 3: Exogenous factors; extracted from Gatfield (2005, p. 316)

Candidate variables	Various
Research skills	Second supervisor contribution
Organizational skills	Shared supervision intra-departmentally
Self-directed agenda	Committee or referents' input
Academic development	-
Research independence	-
Interpersonal skills	-
Respect in relationships	-
Dependency on group or supervisor	-

This study recognised that exogenous factors could influence the specific style preferred by supervisors or students, in the same way that external factors may influence student success (Subotzky & Prinsloo, 2011). Although follow-up studies could investigate whether exogenous factors influence student needs or supervisor preference, the focus of the current study was limited to investigating the influence of the supervision relationship on the time to completion of master's and doctoral students. For this reason, it is necessary to define supervision relationships by comparing the supervision style needs of students and the style preferences of supervisors. According to Gatfield's (2005) combination of structure and support, the supervision styles are expanded upon below.

3.3.2.1. Structure

Structure within supervision relationships refers to a restricting function that limits or guides students' work (De Kleijn et al., 2012; Gatfield, 2005; Khosa et al., 2019). This ensures that students' work conforms to academic, institutional, or disciplinary requirements (Anderson et al., 2006; Gatfield, 2005). Wichmann-Hansen and Herrmann (2017) conceptualised this process as giving advice and expecting that this advice will be taken into consideration. Although the role of the structuring factor is conceptualised differently among authors (Wichmann-Hansen & Herrmann, 2017), it is meant to assist students in learning how to become proficient researchers or scholars (Gatfield, 2005).

Different authors have used various labels to describe factors that seem to conceptualise the same core function. Boehe (2016) defined this as the process factors, and suggested in their model that different supervisors may provide a different amount of direction in the supervision relationships. Wichmann-Hansen and Herrmann (2017) refer to directive and non-directive supervision. In turn, the challenge concept utilised by Greene (2015) highlights the difficulties students may need to overcome throughout their academic development. Whereas even the functional approach described by Lee (2007, 2008) or the machine metaphor described by Grant et al. (2014), expanded on in the product focused theories, could be argued as extensions of the structure factor. Examples of frameworks that share the abovementioned pattern are summarised in Table 4.

Table 4: Literature related to Structure

Factor similar to Structure	Author(s)
Challenge	(Greene, 2015)
Control	(De Kleijn et al., 2012)
Controlling	(Murphy, 2009; Murphy et al., 2007)
Expert coaching and facilitating	(Pearson & Kayrooz, 2004)
Hands-on supervision	(Deuchar, 2008; Gurr, 2001)
Hands on / hands off	(Sinclair, 2004)
Influence (dominance or submission)	(Mainhard et al., 2009)
Interaction incidence	(Grover & Malhotra, 2003)
Research practice-oriented	(Franke & Arvidsson, 2011)
Shaping	(Anderson et al., 2006)
Stability	(Vilkinas, 2002)
Task-focus	(Vilkinas, 2008)
Structure	(Khosa et al., 2019)

Structural factors can thus be viewed as directly influenced by the supervisor, and seemingly act as guidance or boundaries for the student’s work. These limits are mostly set in negotiation with the students, and act to manage the research process and the student’s writing (Gatfield, 2005; Mouton et al., 2015). According to Gatfield (2005), the structural factor, as used in this study, can further be subdivided into three processes, namely: organisational; accountability and stages; and skills provision (Gatfield, 2005).

The **organisational** processes include administration around supervision, as imposed by the institution, or those processes put in place by the supervisor in their preference for student supervision. Although the institution may impose certain elements onto the supervision relationship, this study assumes that students might not perceive a difference between organisational requirements and supervisor preferences. Thus, potentially viewing supervisors as responsible for organisational factors (Table 5). Different elements of the organisational processes may include the way in which students are selected, student-supervisor meetings, and supervisor availability (Gatfield, 2005). **Accountability and stages** refer to the negotiation process, setting up timeframes and turnaround times, and arrangements around publications and research outputs (Gatfield, 2005). **Skills provision** is concerned with providing students with the correct guidance regarding using methodologies, writing, and practical research skills in data analysis (Table 5). Thus, the guidance provided by the supervisors is not limiting in the sense that it hampers the development of students. Instead, it provides direction for their development, so as to align with their institution, discipline, and students' development as academics (Gatfield, 2005).

Table 5: Structural factors; extracted from Gatfield (2005, p. 315)

Organizational process	Accountability and stages	Skills provision
Selecting candidate	Contractual arrangements	Methodologies
Identifying roles	Negotiated meetings evaluation	Writing
Negotiating meetings	Milestones evaluations	Statistics training
Setting the topic	Establishing time frames	Computer software
Setting stages and goals	Staged write-up	Oral presentations
Scheduling group meetings	Supervisor turn-around time	Time management
Recording meetings	Supervisor stage feedback	Short training seminars
Progressive reports	Reports evaluation	-
Supervisor availability	Oral defence	-
Consistent contact	Colloquiums evaluation	-
Supervisor input	Conference evaluation	-
Changing supervisor role	Publications	-
Maintaining focus	-	-
Colloquiums and conferences	-	-
External reference	-	-
Group supervision	-	-
Informal structure	-	-
Time flexibility	-	-
Supervisory model	-	-

Mouton et al. (2015) have argued that the structural aspect of Gatfield's (2005) framework could include the locus of decision-making and degree of monitoring. The locus of decision-making refers to how much responsibility students can take in setting the pace for their studies. The degree of monitoring refers to how closely supervisors monitor students' work (Mouton et al., 2015). This is an intriguing view of the structural factor, since it can place the responsibility in either the hands of the supervisor (increasing the structure), or the student (decreasing the structure). However, Mouton et al. (2015) did not explicitly test the framework and focused only on the main categories or dimensions.

Gatfield's (2005) subdivision of structural factors elaborates on the behaviours that would be considered increasing or decreasing the relationship structure. Boehe (2016) created subdivisions for the conceptually similar process factors in order to predict the increase or decrease of direction. Boehe (2016) proposed that an increase in uncertainty and an increase in organisational complexity may decrease the directedness of a supervisory relationship (and vice versa). Following this argument would imply that doctoral education ought to receive less structure than a coursework master's degree, for example. Arguably, a higher structure element is implicitly present in the curriculum design of coursework master's qualifications. However, this was not found to be the case at the University of Johannesburg. Fourie (2016) used a survey based on Gatfield's (2005) framework, where the findings suggested that doctoral candidates experienced more structure than do coursework master's degree students. Several explanations may be presented, in the sense that doctoral candidates are more aware of how the system functions, or that there are higher incentives for institutions and supervisors who graduate more doctoral students.

Furthermore, Boehe (2016) does not go into depth to define these relationships into operationalised actions, but rather, explains how relationships should ideally function. Such an idea can be seen in the curriculum structure of students, attributing a higher level of skill and expectation to more qualified students. However, Boehe (2016) does not quite present the way in which each factor may explain uncertainties within a supervisory relationship.

Attempting to predict the dominant relationship style based on several factors may have long-term application as an investigation and monitoring tool for master's and doctoral supervision. However, the subdivisions that Boehe (2016) provides do not lend themselves to be operationalised for the current study. Rather conceptualising Structure as a set of tasks performed by supervisors or neglected in less structured relationships (Gatfield, 2005) provides a more robust framework for comparisons required by the study. In future research, noting differences based on degree level (uncertainty), or supervision complexity (individual supervision compared with group supervision), may provide the evidence required to corroborate Boehe's (2016) theoretical perspective.

3.3.2.2. Support

Support, within this context, refers to a non-directive and optional availability of various forms of assistance or access (Gatfield, 2005). The supporting function may be supplied by the supervisor or the institution (Mouton et al., 2015). Within the context of ODeL, students are often required to access such support via their supervisors. Given the way in which supervisors are positioned as a contact point, this may affect students at distance education institutions. As a result, the student may hold supervisors responsible for the support they receive throughout their academic journey. De Kleijn et al. (2012) define the supportive function as the degree to which supervisors can be considered emotionally involved in the project or the progress of their students, which is similar to the personal commitment concept presented by Anderson et al. (2006).

Providing support or access to students is focused on giving them the freedom to grow and develop at their own pace (Gatfield, 2005). An additional function of this approach is that supervisory relationships are maintained by caring for students' well-being and emotional needs, or building relationships with students (Gatfield, 2005; Khosa et al., 2019).

Similarly to the Structure factor, various authors ascribe different labels to factors that seem to share a core function. Boehe (2016) defined the supportive element within this framework as Product factors, also making explicit use of the term Support to describe the influence of this factor. Wichmann-Hansen and Herrmann (2017) conceptualised the element as an Interpersonal Relationship. In this description, even the mentoring approach described by Lee (2007, 2008) or the coach and journey metaphors described by Grant et al. (2014), previously introduced as product focused theories, could form extensions of the Support factor. Additional examples of frameworks that share the abovementioned pattern are summarised in Table 6.

Table 6: Literature related to Support

Factor similar to support	Author(s)
Affiliation	(De Kleijn et al., 2012)
Autonomous or dependent	(Deuchar, 2008)
Distanced or familiar (professional or social)	(Sambrook et al., 2008)
Flexibility	(Vilkinas, 2002)
People-focus	(Vilkinas, 2008)
Interaction style	(Grover & Malhotra, 2003)
Mentoring and sponsoring	(Pearson & Kayrooz, 2004)
Proximity (opposition or cooperation)	(Mainhard et al., 2009)
Pull or push approach	(Wright et al., 2007)
Research relation-oriented	(Franke & Arvidsson, 2011)
Support	(Greene, 2015; Khosa et al., 2019)
Supporting	(Anderson et al., 2006)
Task- or person focused	(Murphy, 2009; Murphy et al., 2007)

The Support factor is thus indicative of the provision of more resources for the development of students, which may take the form of cognitive or emotional support (Gatfield, 2005). As Gatfield (2005) proposes, the support factor can be subdivided into processes that provide more detail to this context, namely: pastoral care; material; financial; and technical support (Table 7).

Pastoral care includes mentoring approaches, encouragement, being more sensitive to students' needs, and providing emotional support, which may consist of lessening restrictive structures. This process is concerned with the relational well-being of students and encompasses the resources that students may need for their personal and academic growth (Gatfield, 2005). **Material** resources like office space, necessary equipment, or academic sources that students may require as part of their discipline or research focus area (Gatfield, 2005). **Financial** support makes funds available for various activities, such as conference attendance or research. Funding access may include financial assistance from industry or scholarships (Gatfield, 2005). **Technical** resources refer to access to software support or support with the processing of the technical aspects associated with a student’s work (Gatfield, 2005). The support provided is not necessarily blanket support, since the needs of students may differ, opting instead for a tailored aspect to the provision of resources (Gatfield, 2005).

Table 7: Support factors; extracted from Gatfield (2005, p. 316)

Pastoral care	Material	Financial	Technical
Proactive supervisor	Office space	Research funds	Statistics software support
Sensitivity to candidate needs	Equipment	Conference funds	Software
Mentoring	Email	Industry funding	Network support
Guidance; keeping on track	Photocopying	Scholarships	Supervision training programme
Morale raising	Policy manual	-	-
Encouragement	PhD handbooks	-	-
Confidence building	-	-	-
Inspiring to persist	-	-	-
Positive feedback	-	-	-
Problems assistance	-	-	-
Group support	-	-	-
Two-way commitment	-	-	-
Interactivity	-	-	-
Complementary research sharing	-	-	-
Supervision sharing	-	-	-
Exposure to academics discipline	-	-	-
Informal meetings	-	-	-

Like the structured approach, Boehe (2016) subdivided the conceptually similar Product factors into several predictive variables for the Support measurement. Boehe (2016) proposed that when supervisors’ power and expertise are considered greater than their student’s, and when supervisors share similar goals with their students, this may increase the supportive nature of their relationship. Stated differently, supervisors with more experience who are interested in their students’ work are predicted to be more supportive in their interactions. Arguably, supervisors who have successfully supervised more students to completion and have higher publication counts (as a metric of power and expertise) may be more aware of the support required within supervisory relationships. In addition, if there is a convergence between the interests or goals of the student and supervisor, the supervisor may be more attentive. This approach also suggests that without such expertise or interests, supervisors would (likely) not be as supportive (Boehe, 2016). This hypothesis was not supported by Fourie's (2016) results at the University of Johannesburg. Although results indicated a variety of approaches to the experience of Support, a clear distinction was apparent due to the qualification type and level (Fourie, 2016), which would conceivably not have existed within Boehe's (2016) explanation.

Furthermore, this explanation does not seem to account for absent supervisors who may not have the time or willingness to attend to each of their students (regardless of fit) (Mouton et al., 2015). Again Boehe's (2016) predictive variables may, in future, assist in monitoring supervisory relationships. However, evidence of support's role in these relationships may require clarification first. Since Boehe (2016) does not operationalise the concept of Support as a measurable set of variables, this study employed the view proposed by Gatfield (2005) to measure this factor.

3.3.2.3. Supervision framework

The conceptual model as proposed by Gatfield (2005) forms the foundation of this project's theoretical understanding of supervision relationships. Gatfield's (2005) conceptual model interprets Structure and Support factors on two continua and provides sufficient detail of each factor to operationalise and validate in a research instrument. The factors are organised on a two-axis grid that identifies four quadrants, representing four distinct supervisory styles. The dominant elements within each quadrant (or style) are grouped into character types of the supervisory relationship. However, more nuanced interactions between the scales may result in complex relationship variations (Boehe, 2016; Gatfield, 2005; Wichmann-Hansen & Herrmann, 2017). The abovementioned theoretical organisation of supervision styles mirrors how other authors have envisioned models of supervision relationships (Boehe, 2016; Brew, 2001; Grover & Malhotra, 2003; Mainhard et al., 2009; Murphy, 2009; Murphy et al., 2007).

The distinction between the four styles proposed by Gatfield (Figure 11; Table 8) was succinctly explained in Mouton et al. (2015):

- **Low Structure – Low Support (Laissez-faire)**: Supervisors who use this style provide minimal direction or support (Table 8). This requires students to be independent in their work and self-motivated. However, this style can also be interpreted as uninvolved and uncaring (Mouton et al., 2015). Harwood and Petrić (2020) refer to this style as non-interfering. It assumes that students can manage their research progress themselves (Deuchar, 2008; Johansson & Yerrabati, 2017).
- **Low Structure – High Support (Pastoral)**: Supervisors who use this style (Table 8) are not necessarily task-oriented, and do not strongly direct the research process, but provide a great deal of support and care for their supervision relationships (Mouton et al., 2015). Students are viewed as capable of managing their projects. However, they still require support throughout their academic journeys (Deuchar, 2008; Johansson & Yerrabati, 2017).
- **High Structure – Low Support (Directional)**: Supervisors who use this style provide a great deal of structure (Table 8), which may be apparent through regular meetings or a highly interactive relationship. However, they prefer to stay on task and focus on the research process. For this reason, they might miss opportunities to provide support or realise when it is needed (Mouton et al., 2015). Students are thus viewed as capable of managing their personal needs and development; however, they require more assistance managing their projects (Deuchar, 2008; Johansson & Yerrabati, 2017).
- **High Structure – High Support (Contractual)**: Supervisors who use this style provide a great deal of structure and support (Table 8). They attempt to use management skills in addition to developing good interpersonal relationships with students. This additionally requires a significant amount of time and effort from the supervisors (Mouton et al., 2015). The contractual style requires some negotiation with students on the amount of structure and support they need. This approach provides project management and supportive engagements via the supervisory relationship (Deuchar, 2008; Johansson & Yerrabati, 2017).

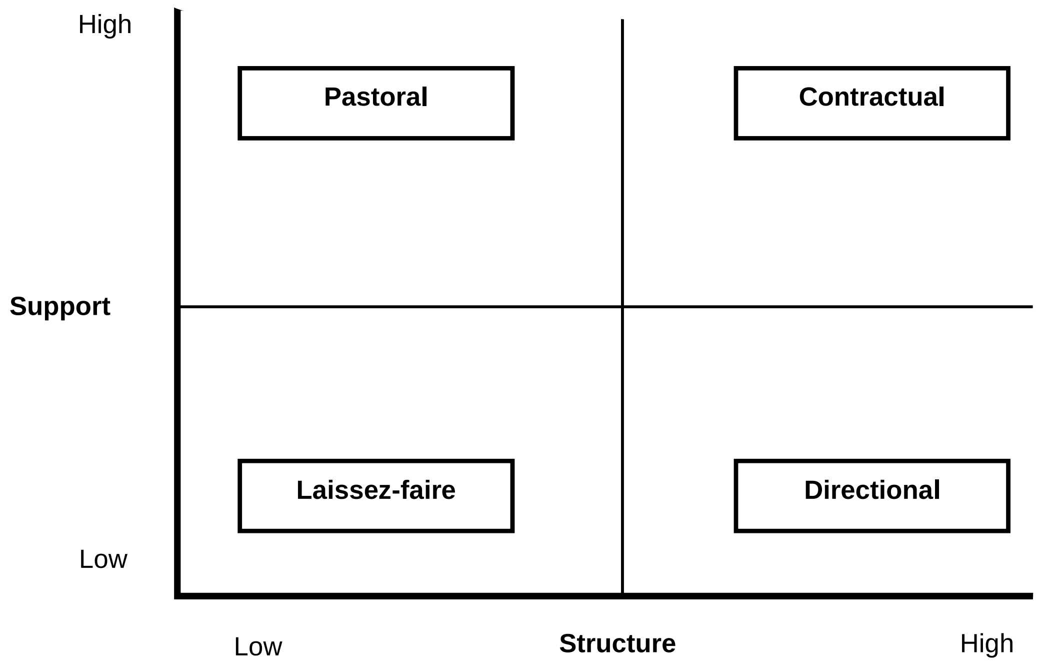


Figure 11: Supervisory management grid, extracted from Gatfield (2005, p. 317).

Table 8: Gatfield's classification extracted from Fourie (2015, p. 6)

	Pastoral Style	**Contractual Style**
High Support	• Low structure and high support. • Students has personal low management skill but takes advantage of all the support facilities that are on offer. • Supervisor provides considerable personal care and support but not necessarily in a task-driven, directive capacity.	• High structure and high support. • Students are highly motivated and able to take direction and to act on own initiative. • Supervisor able to administer direction and exercises good management skills and interpersonal relationships.
	Laissez-faire Style	**Directional Style**
Low Support	• Low structure, low support. • Student has limited levels of motivation and management skills. • Supervisor in non-directive and not committed to high levels of personal interaction. • Supervisor may appear uncaring and uninvolved.	• High structure and low support. • Student highly motivated and sees the necessity to take advantage of engaging in high structural activities such as setting objectives completing and submitting work on time on own initiative without taking advantage of institutional support. • Supervisor has a close and regular interactive relationship with the student, but avoids non-task issues.
	Low Structure	**High Structure**

By way of contrast, Vilkinas (2008) conceptualised the two elements (structure and support) as opposing sides of the same pole, which crossed an internal-external axis to form the four quadrants. However, this positioning seemingly created contradictory roles. Franke and Arvidsson (2011) later argued for a similar distinction of supervision roles, according to a single axis, between research practice-oriented supervision on the one hand, and research relation-oriented supervision on the other. This suggests that supervisors cannot simultaneously focus on students as people and be task-driven to complete their qualifications (Franke & Arvidsson, 2011; Vilkinas, 2008). Sinclair (2004) distinguishes between involved, hands-on and uninvolved hands-off supervision. Relationships were defined by how involved supervisors needed to be, where some students could manage more independence within their work, and others needed more substantial guidance (Sinclair, 2004). Nonetheless, Gatfield's (2005) conceptual model provides a clearer distinction on how supervision relationships may be measured. The model furthermore proposes that supervision styles are flexible, and may change during students' academic journeys, and thus is used as the theoretical basis for this thesis (ibid.).

Throughout a student's academic journey, it is expected that the amount of structure and support they may need or receive may shift (Connell, 1985; Gatfield, 2005; Sambrook et al., 2008), naturally changing the nature of their supervision relationships (Benmore, 2016; Gatfield, 2005; Ward & Brennan, 2018). Similar arguments were made by authors that students' autonomy will grow as they gain experience (Anderson et al., 2006; Benmore, 2016), and that supervisors need to ensure they balance between control and neglect (Benmore, 2016; Gray & Crosta, 2018).

Since the supervision relationship is also influenced by the needs and requirements of students (Gatfield, 2005; Schulze, 2011; Vilkinas, 2008), supervisors may actively adapt their supervision styles as they interpret students' needs and the educational context within which they work (Kumar & Johnson, 2017, 2019). Mainhard et al. (2009) argue that the supervision style of supervisors can only be understood as these relate to a specific student. Effectively arguing that each supervision relationship is unique (Anderson et al., 2006; Kandiko & Kinchin, 2012).

Although flexibility within the supervision relationship is desirable, and sometimes necessary, the opportunity for dynamic relationships may be limited by either institutional or personal elements (Khosa et al., 2019). For example, supervisors may start implementing more structural strategies, where students do not meet their deadlines (Khosa et al., 2019). As described above, the amount of structure and support may shift throughout students' academic journeys (Gatfield, 2005; Mouton et al., 2015). However, supervisors likely prefer a particular style (Benmore, 2016; Gatfield, 2005; Mouton et al., 2015), which may have an underlying influence on their interactions with students.

Within the organisational literature on contingency theories in leadership, Lorsch (2010) argues that leadership approaches (preferred styles) constitute manifestations of individual personality. Thus supervisors would not be able to change their preferred style, but rather gain a deeper understanding of it. Although supervision styles may not manifest within such rigid parameters, such an argument highlights the influence of exogenous factors on supervision relationships (Gatfield, 2005). A supervisor's (in)ability to change supervision style may rest on their interpretation of the purpose of master's and doctoral supervision (Vilkinas, 2008; Wright et al., 2007), which is often informed by their own experiences of being supervised (Kumar & Johnson, 2017; Lee, 2007; Vereijken et al., 2018). Nonetheless, various stakeholders (supervisors, students, and institutions) may have different views on how supervision relationships ought to function (Harwood & Petrić, 2020; Khosa et al., 2019; Vilkinas, 2008).

With the increased focus on master's and doctoral supervision, higher education institutions may be prone to attempt homogenisation of the supervision process through policy changes or the implementation of supervisory guidelines. Supervision guidelines ensure that students receive the same treatment and attention, but may interfere with the individual needs of students, particularly since such institutional policies would not be able to account for the experience of supervisors and students, nor the complexity of the work in which students may be involved (Al-Muallem et al., 2016; Harwood & Petrić, 2020). This highlights the importance of flexibility throughout the student's academic journey (Gray & Crosta, 2018; Gurr, 2001), particularly in strengthening master's and doctoral supervision (Johansson & Yerrabati, 2017).

Supervisors and students need to share an understanding of their supervision relationship. Such a shared understanding (congruence) increases student satisfaction and resilience throughout their academic journeys (Edwards & Billsberry, 2010; Pyhältö et al., 2015; Su et al., 2015) and assists in avoiding possible problems within their relationships (Pyhältö et al., 2015). In this way, congruence may be argued to increase successful outcomes for students.

In contrast, difficulties in the interactions between students and supervisors could result from a mismatch between the supervisor's preferred supervision style and the student's supervisory needs (Murphy, 2009). The supervision style required by one student may be different from the preferred style of the supervisor (Deuchar, 2008; Kandiko & Kinchin, 2012; Khosa et al., 2019; Mainhard et al., 2009; Pyhältö et al., 2015), whereas changing a preferred approach may take effort to accomplish, or have a knock-on effect on other aspects of the process, such as the time to completion (Murphy, 2009).

As presented in the literature chapter, Murphy (2009) has argued that a mismatch between the approaches of students and supervisors could affect a student's time to completion, after interviewing 17 student-supervisor dyads. It should be noted that Murphy (2009) acknowledges that their sample was too small to confirm this claim. This proposition raises an interesting question, is the supervision style of consequence, or is the match between the approaches of students and supervisors important. The supervisory relationship (either positive or negative) was cited as one of the most prevalent themes reported by 2009 doctoral candidates in South Africa when asked about their doctoral experiences (ASSAf, 2010). Fourie (2016) furthermore indicated that they had found a link between supervision styles and time to completion, suggesting the relevance of investigating such interaction within an ODeL context.

Adapting supervisory styles to match students' perceived needs is not necessarily easy (Vereijken et al., 2018) and cannot be done uncritically. Mainhard et al. (2009) suggest that supervisors who increasingly provide structure to their students may be creating dependent students. As a possible response to institutional homogenisation of the supervision process, increasing or decreasing aspects of the supervision style may threaten student progress (Bastalich, 2017). At the same time, continued mismatches in supervision relationships may lead to poor completion rates (Deuchar, 2008; Lee, 2007). This is consistent with results reported by De Kleijn et al. (2012), who suggest that specific outcomes may be related to different aspects of the supervisory relationship.

Findings suggest that students' experience of Structure and Support may influence their satisfaction with the supervisory relationship, and the way in which they perceive their supervisors contributed to their learning and final grades (De Kleijn et al., 2012). It should be noted that in the context of De Kleijn et al. (2012), supervisors were involved in marking their students' work, which may place the independence of the grade observation into question. The findings additionally provided evidence to indicate that the emotional involvement of supervisors is not part of non-professional behaviour. Instead, it forms an essential aspect of the learning experience (De Kleijn et al., 2012). Students seem to feel more supported and motivated if their relationships with their supervisors are defined by being friendly and helpful (De Kleijn et al., 2014). Nonetheless, some authors within the literature argue for a particular style (Khosa et al., 2019), claiming that more involved supervision relationships are more positive or constructive and result in shorter completion times (Sinclair, 2004).

It may be argued that Gatfield's (2005) supervision theory requires more extensive empirical testing so as to ensure that the claims derived from this framework are reflected in the supervisory context. Such testing is crucial, considering claims are made either for or against particular styles (Fourie, 2016; Sinclair, 2004), specifically between student-supervisor dyads (Murphy, 2009). Preliminary results seem promising internationally (Murphy, 2009) and within the context of South Africa in particular (Fourie, 2016; Mouton et al., 2015). This framework, additionally, seems useful specifically within ODeL education, where master's and doctoral supervisors may be placed in a more influential position as the primary contact point for students, highlighting the importance of a trusting relationship (Gray & Crosta, 2018; Kumar & Johnson, 2017, 2019; Orellana et al., 2016).

Thus, some authors argue (Gatfield, 2005; Schulze, 2011) that experienced supervisors and new supervisors ought to receive training to identify their preferred supervision styles. This model may pair students entering the master's and doctoral degree programmes with potential supervisors (Gatfield, 2005; Golde, 2005; Orellana et al., 2016). It may be the case that attempting to match preferred styles might not be ideal, due to the limited supervision capacity available in the South African context (ASSAf, 2010). Instead, the knowledge about the preferred supervision styles may provide supervisors with the required information to manage their relationships with their students more effectively. Alternatively, Andriopoulou and Prowse (2020) critique such supervision theories because they conceptualise supervision as simplistic relationships that only involve the supervisor and student. This excludes factors that have been considered by other researchers that relate to power dynamics in supervision, or the effects of different personality traits (Andriopoulou & Prowse, 2020).

3.4. Chapter summary

This chapter presented technical aspects of theoretical and conceptual frameworks in order to understand supervisory relationships in master's and doctoral education. This consideration of theory provides a critical foundation for this study. However, it should be reiterated that supervision relationships are not technical, pedagogical tools, but human relationships within an educational context (Connell & Manathunga, 2012). As previously described by Connell (1985), supervision needs to be viewed as primarily an act of teaching (Connell, 1985; Orellana et al., 2016; Vereijken et al., 2018), which can become an intense relationship for supervisors and students. The theoretical components discussed are nonetheless required in order to provide a basis for the creation of measurements for the current study and, as such, require a more technical presentation.

Towards this end, this chapter integrates fit theory (Baker & Pifer, 2015) with the contingency theory of supervision proposed by Gatfield (2005). The proposed combination of the two theories does not oppose to the socio-critical model that maps student success at Unisa. However, the proposed frameworks highlight factors unique to the supervision relationship between master's and doctoral students and their supervisors. This emphasis provides context for the study, focusing specifically on the relationship between students and their supervisors. By retaining the view of supervisors and students as individuals, the current use of these theories is consistent with the framework proposed by Subotzky and Prinsloo (2011). Unique interactions in supervision relationships ensure that students are successful in their studies. Students and supervisors are still viewed as autonomous agents, where supervisors represent the institution's agency, from their students' perspectives. The relationship functions within a broader system that to some extent intrinsically provides structure (the qualification curriculum and academic year) and support (through additional supportive initiatives like workshops and student counselling). However, combining the theory of fit and contingency theories of supervision provides a new perspective of the supervision relationship that may assist in measuring how students navigate the student-walk, as proposed by Subotzky and Prinsloo (2011).

Chapter 4: Method

The following chapter provides an overview of the methodological considerations in investigating the relationship between the student-supervisor fit and the time to completion of master's and doctoral students. The purpose statement is reiterated with the research questions in order to provide a starting point for the discussion. The research paradigm is briefly introduced so as to provide a foundation for the methodology. An outline of the population and a description of the study's final sample is provided, as well as a description of the instrument development and process employed during the data collection. The analytical processes utilised to investigate the validity and reliability of the research instruments are examined. The results from this analysis are presented in the following chapter. The chapter concludes with a discussion of the approach used to analyse the data to answer the research questions and provide a brief outline of the research ethics applied to this project.

4.1. Research questions

This study aims to measure the relationship between student-supervisor fit and time to completion of students in master's and doctoral education. The nature of the study is exploratory, and as such, the research questions to address this purpose are:

- RQ 1: Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?
- RQ 2: Is there a difference between the supervision style preferences of master's and doctoral students?
    - RQ 2.1: Is there a relationship between the supervision style preferences of master's and doctoral students and their time to completion?
- RQ 3: Which factors influence the supervision style preferences of master's and doctoral supervisors?
- RQ 4: Is there a relationship between the congruence of supervision relationships and the time to completion of master's and doctoral students?

4.2. Research paradigm

The research focus of this study assumes that supervision relationships are measurable, and can be used to determine student-supervisor fit. The assumption is further made that the measured fit could be related to students' time to completion of their qualifications. This underlying assumption is consistent with a positivistic research paradigm (De Vos et al., 2011). The positivist paradigm bases research on the ontological perspective that reality exists externally and independently of observation or personal experience. This view maintains that there are law-like rules that govern everything. The reality remains constant, and does not change without an event that can be attributed as the cause of such a change (De Vos et al., 2011; Terre Blanche et al., 2006). This perspective of reality results in the epistemological belief that reality can be observed, measured, and recorded. Such observation is believed to be objective (as close to the conception of objectivity as can be attained), and it is possible to be neutral, and not interact with the observed phenomenon (De Vos et al., 2011; Terre Blanche et al., 2006). Although this paradigmatic position has been critiqued at length in the social sciences, referring to the problematic claim of objectivity and belief in a single discoverable 'truth' (De Vos et al., 2011; Terre Blanche et al., 2006), the position typically remains the basis for quantitative research (De Vos et al., 2011; Terre Blanche et al., 2006). This position thus provides a basis for the belief that social interactions can be measured and provide evidence for validating social theories or alternative explanations for behaviours.

However, the epistemological foundation only considers phenomena that can be observed as possible sources of knowledge. This further means that quantitative research is typically deductive, and requires theoretical explanations to investigate specific phenomena (De Vos et al., 2011), as introduced in the previous chapter. Such a philosophical foundation directly impacts the possible research designs available to investigate the relationship between student-supervisor fit, and time to completion, during master's and doctoral studies. However, the approach is consistent with the way in which Boehe (2016) previously conceptualised a similar project on supervision styles.

4.3. Research design

The research design of the project was correlational, and primarily focused on investigating relationships between variables (De Vos et al., 2011; Field et al., 2012). Within this study, the variables of interest were supervision fit and time to completion of master's and doctoral students. Correlational studies are somewhat limited in the sense that causal relationships cannot be inferred between the variables under investigation (De Vos et al., 2011). Nonetheless, a correlational design was selected for this study due to its possible ecological validity[28] (Field et al., 2012). Students or supervisors may, in practice, approach one another in forming their supervision relationships, which would have been absent within experimental designs that may have provided a causal argument. Instead, exploring supervision fit within existing relationships would arguably provide more practically relevant information, since it is impossible to replicate such relationships artificially.

So as to ensure minimal interference with the supervision relationship and research progress of students, a cross-sectional project was conducted, primarily making use of an online questionnaire and access to available staff and student records in order to collect data. This was consistent with the view that cross-sectional research uses observations without direct interference (or as minimal a degree of interference as possible). One limitation of such studies is that cross-sectional research only considers information at a single point in time (De Vos et al., 2011; Field et al., 2012), where it is typically used to provide evidence for the consistency of theoretical perspectives (De Vos et al., 2011). This approach limits the investigation to a single collection time, whereas supervision relationships are often considered fluid. The focus of this study was thus explicitly placed on preferred supervision styles, ensuring that the methodological approach was ideal for the current project.

Data for this study was collected online with a questionnaire distributed to master's and doctoral students and their supervisors. The questionnaire was a self-report measurement, intended to provide data that could be used to create an index of

[28] Ecological validity refers to the possibility of applying research results to real world conditions (Field et al., 2012).

supervision preferences. These indices were used to infer information about the supervision relationship fit. Questionnaires are typically used to gain more information about a particular phenomenon, and the validity can be investigated to increase confidence in their findings (De Vos et al., 2011). The creation and validation procedure of the instrument is discussed later in this chapter (see section 4.6). The questionnaire was distributed via SurveyGizmo,[29] an online survey hosting platform. An online survey platform was deemed ideal for this study due to practical and logistical considerations around data collection and capturing (De Vos et al., 2011). Also, Unisa students typically study online.

4.4. Population

Higher Education Institutions provide annual audited statistics on all student enrolment, graduations and staff data, as part of the Higher Education Management Information System (HEMIS), which is used in the allocation of governmental subsidies (Department of Higher Education and Training, 2020a; Styger et al., 2015). The aggregated data is publicly available, and thus functions as the source of the population estimates of this project. Although the HEMIS counts may differ slightly from current enrolment information, due to the inclusion criteria and census dates, the HEMIS statistics are audited so as to ensure accurate calculation of higher education subsidies. This data was accessible through the peer data reports provided on the IDSC website (IDSC, 2021a, 2021c, 2021d). The data was used to estimate students' and supervisors' possible population size.

4.4.1. Students

Students were considered part of the study population if they were registered for a master's or doctoral degree in 2019. Alternatively, if they graduated with a master's or doctoral qualification from Unisa in 2019, or within the preceding two years (i.e., 2017, 2018, 2019), it was considered that alumni who completed within these three years would

[29] SurveyGizmo was rebranded as Alchemer® in 2020 (www.alchemer.com).

still be contactable, as well as still being familiar with what their supervision preferences were during their studies. All enrolled master's and doctoral students were invited to participate so as to ensure an adequate sample size. Since it was possible that respondents enrolled for a master's or doctoral qualification during 2019 may have been able to complete their studies within this project's timeframe.

According to the publicly available peer data, there were, in total, 7 501 students enrolled for qualifications at doctoral (2 481) and master's (5 020) levels at Unisa during 2019 (Table 9). During the years of interest (2017-2019), there were a total of 3 626 graduates at the doctoral (938) and master's (2 688) levels. There were around 300 doctoral graduates per year for the years specified, specifically 289 (2017), 314 (2018), and 335 (2019). While master's graduates at Unisa were numbered around 800-900 per year, specifically 931 (2017), 956 (2018), and 801 (2019). Overall, around 1 200 master's and doctoral graduates were awarded their qualifications within each year of interest (Table 10). Consequently, the total student population for the current project can be estimated[30] as 11 127.

Table 9: HEMIS Unisa master's and doctoral student enrolments 2019 (IDSC, 2021d)

Qualification type	Enrolment headcount
Doctoral	2 481
Master's	5 020
Grand Total	7 501

Table 10: HEMIS Unisa master's and doctoral graduates 2017, 2018, 2019 (IDSC, 2021a)

Qualification type	2017	2018	2019	Grand Total
Doctoral	289	314	335	938
Master's	931	956	801	2 688
Grand Total	1 220	1 270	1 136	3 626

[30] Given that the estimate includes multiple academic years, it is possible for students who enrolled for a doctorate directly after completion of a master's may have been counted twice.

4.4.2. Supervisor

The number of master's and doctoral supervisors in higher education is currently more difficult to estimate. Although staff numbers, employment, and qualifications are reported as part of the HEMIS reporting cycles, HEIs are not required to report on master's and doctoral supervision specifically. Supervisors are typically academic or teaching staff because their position in the institution requires that they take up such a role; however, support staff can also take on supervision roles. The University additionally employs external supervisors under certain conditions, although typically in a supporting co-supervision capacity. Supervisors need to be at least qualified at the same level they supervise. Only staff who have obtained master's and doctoral qualifications can be considered. During the 2019 academic year, Unisa employed a total of 1 409 academic and support staff (in a permanent or temporary capacity), who could be considered eligible to act as supervisors for master's or doctoral studies (Table 11).

Table 11: HEMIS Unisa Instructional / research professionals and specialised / support professionals with master's or doctoral qualifications 2019 (IDSC, 2021c)

Staff Headcount	2019
Instructional/research professional	-
Professor	296
Associate professor	262
Senior lecturer	434
Lecturer	346
Specialised/support professional	-
Other than instructional and research professionals	71
Grand Total	1 409

Due to supervision arrangements, it was assumed that each student could be linked to at least one supervisor. Although co-supervision relationships likely impact progress, this project only investigated student-supervisor fit through the primary supervision relationship. It was presupposed that at least one relationship ought to exist with each student included in the data, while supervisors included in the data may have had multiple students. Students who completed master's qualifications and immediately registered for doctoral studies may have been duplicated in the data set. However, each student-supervisor dyad linked through a unique qualification code would be considered a single unit of analysis, due to the relational focus of this study.

4.5. Sample

Due to the accessibility of both supervisors and students, no sampling technique was employed within this project, similar to the approach taken by Ali et al. (2016). Both supervisors and students could be contacted via email from available institutional data, and the advancements in online surveys meant that there was no logistical need to reduce the number of potential respondents. Consequently, the study used a census approach (Jupp, 2006), and the study sample depended on the number of students and supervisors who voluntarily responded to the online surveys. Contact information was considered private, where invitations were sent from the University ICT Department. A total of 11 762 email invitations were sent (P. Ngoepe, personal communication, October 17, 2019) to students who formed part of the project population (all registered master's and doctoral students during the 2019 academic year and all students who graduated with a master's or doctoral qualification between 2017-2019).

Similarly, email invitations were sent to the entire possible supervisor population of the study (amounting to all internal and external supervisors), representing a total of 1 676 email invitations (P. Ngoepe, personal communication, October 17, 2019). In both instances, the number of emails approximately reflected the population estimates calculated above, where likely differences may have occurred due to different inclusion criteria in the HEMIS submissions, multiple email contact information, or the fact that some supervisors were not directly employed as staff members. Although no sampling technique was applied, the number of respondents who voluntarily provided unique, complete responses to the online survey was considered to constitute the sample within the current study.

Sample size convention within the social sciences suggests that results may be generalisable if a large enough proportion of a population responds to a survey. However, it is vital to ensure that samples represent a population (De Vos et al., 2011). Using the above estimates for the population size for the study, assuming that an acceptable margin of error would be 5% and that the confidence level of the project was 95%, which are typical assumptions within the social sciences (Field et al., 2012; Raosoft Inc., 2004). The online sample size calculator provided by Raosoft (2004) was used to estimate the desired sample sizes for the study.

Estimates suggest that 373 students were required to respond to the survey so as to ensure enough information was gathered for possible generalisations. Similarly, the project would have required responses from 313 supervisors in order to make similar claims about generalisability. Sampling guidelines provided in the literature provide different criteria as general guidelines, suggesting that 450 or more respondents would be required for a population above 10 000, or that 140 respondents would be enough for a population of 1 000 (De Vos et al., 2011). In addition to the abovementioned sample size estimations for generalising data, the required sample size typically depends on the type of analysis conducted in a given study (De Vos et al., 2011; Field et al., 2012; Likert, 1932; Pallant, 2011). The sample size requirements for the analytical process are discussed further in the relevant sections. However, it is recognised that overall, large samples may be oversensitive, and may provide significant results ensuing from minor differences (which may be due to chance).

In contrast, samples that tend to be too small may miss differences in the data (Hair et al., 2014). This argument is expanded on later in this chapter (see section 4.8.1.). Nonetheless, judging the sufficiency of overall sample sizes remain somewhat open to interpretation (De Vos et al., 2011; Field et al., 2012; Likert, 1932; Pallant, 2011).

During the data collection timeframe (in October 2019), 2 145 master’s and doctoral students and alumni provided responses to the online survey. After removing partial responses, duplicates, and preliminary data cleaning, 1 323 unique, completed records remained within the student dataset (Table 12). The number of responses suggests that a margin of error below 2% could be expected at a confidence level of 99% for students (Raosoft Inc., 2004). A total of 254 responses were initially recorded on the supervisor survey. After removing partial responses, duplicates, and initial data cleaning, 180 unique responses remained within the dataset (Table 12). In contrast, the study did not gain enough support from supervisors to make similar generalised inferences about the supervision population, suggesting that the margin of error may be 6.9% for the 95% confidence level (Raosoft Inc., 2004).

Student and supervisor respondents were requested to provide their student- or staff numbers in order for the data to be linked to available institutional records. Such a provision was required in order to complete the surveys so as to ensure that responses could be linked to their respective supervision relationships. Due to practical constraints, the student and staff numbers could not be authenticated at the time when respondents completed the online questionnaires. As a result, 1 183 of the student responses were linked to available student data, and 169 supervisor responses were linked to staff data.[31] Data points that could not be linked back to provided databases were nonetheless deemed useful for the validity investigation of the research instruments and the project's overall student and supervision profile. Although data may not be linked, the assumption was made that students and supervisors remained honest in completing the instrument. Finally, supervision data was linked to student information per qualification at a modular level, where it was possible to link students and supervisors who completed the online surveys. In total, 137 relationships could be identified within the current data sets. Sixty-nine of the student respondents completed their respective qualifications. Although it is recognised that the lower number of data points at this particular project stage limits possible inferences outside the current sample, the data was considered sufficient to demonstrate the measurement of supervision relationship fit.

Table 12: Response rates

Respondents	Students	Supervisors
Recorded on the online platform	2 145	254
Agreed to participate	1 784	223
Completed the online survey	1 388	188
Study sample (unique responses)	1 323	180
Responses linked to institutional data	1 183	169
# Emails distributed	1 1762	1 676
% Of emails distributed (`rate)	10.05%	10.08%

[31] Institutional data to link responses were requested on two occasions, the first during November 2020, and the second in May 2021 to update any changed records.

4.6. Research instrument

The research data for this project was primarily collected through a self-developed questionnaire intended to measure supervision style preferences according to Gatfield's (2005) theory of supervision. Although it would have been ideal to use an existing standardised instrument so as to avoid the risk of high measurement error (De Vos et al., 2011; Hair et al., 2014), none of the available instruments were consistent with the purpose of this project. Available instruments lacked information about the validity and reliability needed to make such a decision. Therefore, Likert-type questions were developed by operationalising the theoretical framework discussed in the previous chapter.

Likert scales capture expressions of attitude or agreement that can be ranked on a continuum as ordinal categories (Cohen & Swerdilik, 2010; De Vos et al., 2011; Jamieson, 2004; Likert, 1932). Likert scales typically consist of several phrased statements (Likert items), where responses are requested as degrees of agreement on a five-point scale. Adaptions to this structure are often made (De Vos et al., 2011; Jamieson, 2004). Within this project, a seven-point scale was created, consistent with methodological considerations of this approach (Fleming et al., 2013; Jamieson, 2004). Deviating from typical Likert designs, response options on the extreme ends of the scale were worded (strongly agree to strongly disagree); however, response options between these statements were numerical. This served two specific needs in the current study: 1) online survey portals provide a convenient and unique way of structuring survey items. However, available space across different devices, such as tablets or smartphones, does not allow for full-phrased response items (see Appendix B); 2) this form of labelling allowed for a neutral option to be provided to the scale (the number 4) without priming the availability of a neutral option explicitly. Although numerical scoring on Likert items suggests an 'objective' measurement, the numerical assignment reflects purely ordinal-level measurements. Responses to such items can be ranked. However, distances between response values cannot be treated as equal, despite researchers using analytical processes that assume interval-level data (Field et al., 2012; Jamieson, 2004).

Likert (1932) argued that statements should not be factual, but instead measured as desired behaviours, so as to ensure that personal attitudes or preferences are captured, rather than common knowledge. Such statements must be simple and concern only a single concept or thought (De Vos et al., 2011; Likert, 1932). Furthermore, Likert’s (1932) initial instruction on developing such items was to avoid polarised responses, also referred to as biased questions, and instead, to ask questions in such a way that the modal reaction would tend towards the middle of the scale as far as possible. This approach would ensure enough variability in the data for differences or similarities to be investigated, and possibly inferred to the population (De Vos et al., 2011; Likert, 1932). Multiple items regarding similar concepts or constructs allow the researcher to reverse the score on certain items so as to avoid stereotyped responses (Likert, 1932; Podsakoff et al., 2003). However, recent literature does warn against negatively phrased questions (De Vos et al., 2011; Podsakoff et al., 2003). Including more items that are initially required in the measurement allows the researcher to remove unsatisfactory items that may compromise the integrity of the data (De Vos et al., 2011; Hair et al., 2014; Likert, 1932), assisting in reducing the amount of measurement error that is present within the collected data (Hair et al., 2014).

Measurement error is an expected part of any instrument design. It represents the difference between the actual score on a measurement (assumed to exist within the positivistic paradigm, however, impossible to observe) and the observed value (Cohen & Swerdilik, 2010; Hair et al., 2014). There are multiple sources for measurement error within an instrument, including problems with data values and respondents’ ability to reflect on their responses (Hair et al., 2014). It is possible to minimise measurement error. Notably automating the data entry, such as the online survey approach taken within this study, and considering various design options, which will be expanded on below. Although measurement error can, to some extent, be controlled or limited, it is not possible to eliminate it from any research project (Hair et al., 2014).

The psychometric properties of measurements allow researchers to make inferences about the unobservable characteristics of people (Rose et al., 2019), consistent with a positivistic paradigm. However, inferences based on individual questions may be much more susceptible to measurement error, due to random variations in selected response options. In order to reduce the random measurement error of a variable and simplify the analytical process, scales or indices are typically created that combine the information of several related variables that each reflect different aspects of the same underlying construct (Hair et al., 2014). To combine the information from related variables, ordinal response options are assigned a numerical value and can be summed or averaged (De Vos et al., 2011; Hair et al., 2014; Likert, 1932) to create an index score (De Vos et al., 2011). Thus, avoiding individual variables, whilst retaining a well-rounded perspective and providing a way of simplifying data analysis and interpretations (Hair et al., 2014). The resulting index scores are composite measures of related variables often considered at an interval or ordinal level of measurement (De Vos et al., 2011).

Creating an index score reduces random measurement error, as the combination of scores presumes that truly random variations would cancel each other out. However, such an approach would compound non-random measurement error (Hair et al., 2014). There is a multitude of possible sources of bias within questionnaire development. Remedying one source allows another source of bias to influence respondent scores (Podsakoff et al., 2003). This does not imply that all sources of bias are acceptable, but rather, at the very least, that researchers ought to be aware of the limitations present in developing such instruments. Examples of such approaches are to keep the positive and negatively phrased questions balanced, as well as to include more items that are initially needed and remove items that are found to not contribute to the index.

Furthermore, using close-ended questions (such as Likert scales) reduces the range of response options that may be available. However, this may not reflect how respondents feel, or prime respondents for a particular answer (De Vos et al., 2011). The position of items within such measurements has been found to affect responses, where it is not necessarily possible to quantify the magnitude of these effects (Podsakoff et al., 2003; Rose et al., 2019). This effect suggests that item randomisation can be used to mitigate such biases. However, it has also been found that if constructs measured within an instrument are similar, item randomisation may increase inter-construct correlations, and reduce intra-construct correlations (Podsakoff et al., 2003), thereby reducing discriminant validity and introducing a different source of bias into the measurement.

A different approach to avoiding bias is to obtain the data of different variables from different sources. Mainly focusing on the criterion and predictor variables would ensure that artificial relationships are not created due to the measurement method (Podsakoff et al., 2003). This approach was advantageous within the current study. Supervisors and students could respond to questions relating to their preferred supervision styles. At the same time, qualification completion status information is already collected and processed within institutional databases. As a result, each provides an independent source of the required variables. The following section describes the operationalisation of the constructs in the research instrument.

4.6.1. Operationalisation

Taking into account the stated information concerning the design of the measurement, it is important to consider the literature on the constructs related explicitly to the theoretical foundation of what is intended to be measured (De Vos et al., 2011; Hair et al., 2014; Terre Blanche et al., 2006). For this study, the Structural and Supportive factor elements expanded on by Gatfield (2005) formed the foundation of the measurement (see Tables 5 and 7). Question items were required to be related to the theoretical framework and be worded consistently within the context of master's and doctoral supervision at Unisa. Furthermore, it was necessary for the research instrument to be mirrored for supervisors and students, so as to ensure that the same aspects of supervision style preferences were compared.

As previously indicated, several instruments were available that focus on measuring aspects of supervision relationships. Many of these instruments were designed based on Gatfield's (2005) theoretical framework, consistent with this study, or with a comparable framework. The majority of the instruments, however, did not provide evidence of instrument validity on the question structures, typically limited by small sample sizes (Table 13). Although Wichmann-Hansen and Herrmann (2017) utilised both exploratory factor analysis and confirmatory factor analysis, the reported model fit statistics were below conventional thresholds (both analytical processes are expanded on in 4.8.2.1 and 4.8.2.2). Mainhard et al. (2009) made use of the item and construct correlations and reliability analysis; however, due to limited sample sizes, such results would likely be challenging to replicate. Mouton et al. (2015) explicitly indicated that their goal was not to validate Gatfield's (2005) framework, but to describe the supervision experiences of doctoral supervisors. Overall, none of the available measurement tools focused on student or supervisor supervision style preferences. Instead, each considered aspects of the supervision relationship that may be relevant to this study (Table 13).

Table 13: Supervision measurement literature

Author	Theory	Respondents	Item #	Limitation
(Al-Muallem, 2018; Al-Muallem et al., 2016)	Social Cognitive Theory	n = 231 undergraduate and postgraduate supervisors	Total items: 30 After factor analysis: 15 retained 23 of the items (14 of the retained items) corresponded to the content of the instrument utilised in this study	The small sample size limits possible interpretations of validity. Considered supervision self-assessment of readiness; however, included elements not within the control of supervisors (as a needs assessment tool, such questions remained relevant for institutional support).
(Alam et al., 2013)	No formalised framework of supervision relationships	n = 30 master's and doctoral students	Total items: 15 Research supervision: 9 Institutional support: 6	Small sample size No instrument validation was conducted. Questions seemingly focus on procedural aspects of the supervision relationship and broad student satisfaction.
(Ali et al., 2016)	An explorative study which identified factors named: leadership, knowledge, and support The leadership factor shares some Structural components. Knowledge and Support seem to vaguely share elements	n = 208 (131 students and 77 supervisors)	Total items: 30 items, of which 20 were retained.	Small sample size limits interpretations made from the exploratory factor analysis. Items suggested biased responses, where response averages were typically above four on a five-point scale. Student and staff data were not analysed separately. Typically included relatively old literature in the design of the measurement. The authors did not provide an adequate description of the measurement validity.

Author	Theory	Respondents	Item #	Limitation
(Cornér et al., 2017)	Focused primarily on supportive elements: - Supervisory support - Researcher - community support - Equality in the researcher community	n = 248 doctoral candidates	Total of 20 items related to three constructs, where 13 items appear to have been retained.	The study aimed to investigate a possible relationship between students' perceptions of their supervision relationships and burnout. The focus primarily on supportive elements would have been inconsistent with the focus of the current study.
(Fourie, 2016)	Gatfield's theoretical framework	n = 492 master's and doctoral students	Total items: 57 Guidance [Structure]: 42 Support: 15	Evidence of validation of the instrument was not provided. Supportive elements were only related to institutional support. Structural items contained items related to both supervision support and structure.
(Gedamu, 2018)	Measured Directive and Supportive components of supervision based on Gatfield's theoretical framework.	n = 70 graduate students	Total items: 28 Directive supervision: 17 Support: 11	Small sample size No instrument validation was conducted.
(Mainhard et al., 2009)	Constructs: Proximity (opposition – Cooperation) and Influence (submission – Domination) Comparable to Gatfield's model.	n = 98 members of the PhD division	Total items: 41 Eight constructs were created, each measured by four to six independent questions each.	Small sample size No instrument validation was conducted. The instrument focus was not consistent with the underlying assumptions of this study.

Author	Theory	Respondents	Item #	Limitation
(De Kleijn et al., 2012)	Based on the work conducted by Mainhard et al. (2009).	n = 401 master's students	Not explicitly specified The questions focused on measuring perceived interpersonal control and affiliation The study used a confirmatory factor analysis approach which indicated a good fit for a two-dimensional model (control and affiliation): TLI = .96 CFI = .98 RMSEA = .09 The measures indicated relatively good Cronbach's alpha reliability: Control = .78 Affiliation = .93	Instrument based on the study by Mainhard et al. (2009) discussed above. Thus, the instrument focus was not consistent with the underlying assumptions of this study.
(Mouton et al., 2015)	Gatfield's theoretical framework	n = 331 doctoral supervisors	Total items: 19 Structure: Locus of decision making: 7 Structure: Monitoring: 7 Support: 5	The purpose of the study was descriptive. Psychometric properties were not considered. An additional framework of 'locus of decision making' was included in the measurement of supervision.
(Pearson & Kayrooz, 2004)	Research framework comparable to Gatfield's model	Consisted of two samples n = 314 and n = 59 master's and doctoral students (primarily doctoral candidates responded)	Total of 58 items, within five constructs. 41 items were retained.	Small sample size limits interpretations made from the exploratory factor analysis. The instrument's focus on satisfaction was not consistent with the underlying assumptions of this study. Factor loadings did not seem to reflect desired factor structure, somewhat placing a question on the validity of the measure.

Author	Theory	Respondents	Item #	Limitation
(Wichmann-Hansen & Herrmann, 2017)	Measured Directive supervision and Interpersonal relations, conceptually related to Structure and Support.	n = 1 690 doctoral candidates	Total items: 20 Final model: 14 Supervision direction: 8 Interpersonal relation: 6	Item responses tended to be skewed. Confirmatory Factor Analysis fit statistics differed from recommended thresholds.[32] Chi-square test (χ^2 = 506.9, df = 74, p < .001) CFI = .886, RMSEA = .083, SRMR = .090, χ^2/df = 6.85

[32] See Table 15 for recommended goodness-of-fit thresholds.

To provide one example of a comparison that could be made between the instrument used in the current study and one of those found in the literature: Al-Muallem (2018) and Al-Muallem et al. (2016) developed an instrument that could presumably be used as a self-assessment in order to gauge the needs and readiness of staff towards their potential roles as supervisors (Al-Muallem et al., 2016). Despite utilising different theoretical frameworks and methodological approaches, the study highlighted similar topical issues critical to research supervisors as those considered within the current study. i.e., Q_24: “I actively guide each one of my students on how to conduct a literature review” (Table 71),[33] vs. “I have the necessary skills to guide my students to carry out literature search” (Al-Muallem, 2018, p. 269). Aspects of the surveys that were dissimilar were explicitly concerned with institutional oversight, career progression requirements, or subjective opinions of what constitutes a ‘good supervisor’ (Al-Muallem, 2018, p. 269):

- “My student supervision is considered for promotion by my institution.”
- “My institution has a review board overseeing research supervision process and practices.”
- “I believe a good supervisor, should be a researcher as well as an educator.”

It remains challenging to compare studies on supervision due to different focuses and uses in terminologies (Wichmann-Hansen & Herrmann, 2017). However, as expanded in the previous chapter, some similarities cut across the theoretical frameworks of master’s and doctoral supervision. The measurement used within the current study was thus conceptualised first from the constructs of Structure and Support. Each was divided into sub-categories, as envisioned by Gatfield (2005),[34] and initial operationalisation within subcategories was developed as question options. The questionnaires of the studies cited above were matched to relevant operationalisations and considered for adaptation. In this study, care was taken within this process to ensure that questionnaires for both supervisors and students could be created to be as closely matched as possible when it

[33] The questions items were numbered from Q_01 up to Q_51 and are identified in this way throughout this thesis. The full list of questions including the numbering is presented in Table 71.
[34] The theoretical framework formally posits seven sub-themes, however, the sub-theme Technical support was not used in the survey design, as this aspect of master’s and doctoral educational experiences may not typically fall within the ambit of the supervision relationship.

came to the content and phrasing. In total, 51 Likert-type questions were developed on a seven-point scale, 31 of which were conceptualised as part of the Structure construct and 20 as part of the Support construct. Both positive and negatively phrased questions were used in this study (Table 14), which were aimed at limiting response bias where respondents may fall into a habit of selecting only a single response option (response pattern biases) (Leung, 2001; Podsakoff et al., 2003; Rattray & Jones, 2007; Song et al., 2015).

Table 14: Survey conceptual structure

	Negatively phrased	Positively phrased	Grand Total
Structure	**11**	**20**	**31**
Accountability and Stages	3	6	9
Organisation	6	8	14
Skills provision	2	6	8
Support	**6**	**14**	**20**
Financial	-	2	2
Material	1	3	4
Pastoral Care	5	9	14
Grand Total	**17**	**34**	**51**

4.7. Process and data collection

Given that the population was geographically dispersed, an online survey platform was the most effective and efficient method of distributing the questionnaires. The online survey platform additionally allowed respondents to complete the survey in their own time, and the automation of the data collection avoided potential data-capturing mistakes (De Vos et al., 2011). Unfortunately, online surveys tend to have both lower response rates and completion rates. Such systems also require knowledge of how to operate devices able to access such a platform (De Vos et al., 2011). The latter limitation was less of a concern in the study since students and supervisors were assumed to be familiar with and comfortable accessing material online, due to the online nature of the institution.

The survey invitations were distributed via email, from the Unisa ICT offices, on 28 August 2019, with an anonymous generic link to the survey. Distributing the invitations from Unisa ensured that contact information did not need to be shared with the researcher and provided additional legitimacy to the study. A reminder message[35] was distributed on 15 October 2019. A single reminder was allowed within the ethical clearance processes so as to ensure that students and supervisors were not overburdened with communication about this project.

Supervisors and students could follow the link embedded in the email invitation to the informed consent page of their respective surveys. The informed consent page provided an overview of the study's purpose, and linked to PDF versions of all applicable ethical clearance forms. Respondents who wished not to participate could close their web browsers without adverse consequences.

The responses collected from supervisors and students needed to be linked to form relationship dyads, necessitating the collection of identifiable data. Respondents were asked to provide student and staff numbers in order to facilitate this link. External supervisors were asked to provide their email addresses (since they may not have had access to internal personnel codes). The question relating to the identifiable information was the only forced choice option in the survey, and acted as a second acknowledgement of consent to participate.

After providing consent, respondents were directed to the 51 questions regarding their preferred supervision styles. Question items were ordered in a quasi-random order in the survey. Between five and six questions were grouped on a page, resulting in a total of ten pages. Each respondent saw a random order of the ten pages and a random order of the grouped questions on each page, thereby simulating item randomisation. The option was selected to mitigate the item's effect or construct positioning as a potential bias, as previously discussed (Podsakoff et al., 2003; Rose et al., 2019).

After completing the 51 questions on supervision style preferences, respondents were routed to the biographical section of the survey. Each questionnaire included additional biographical questions so as to limit the number of variables required from institutional

[35] It was initially planned to send the reminder after two weeks. However, technical difficulties on the SurveyGizmo platform creating server instability resulted in a delay (SurveyGizmo Customer Support, personal communication, August 30, 2019).

data. Consistent with research best practices and POPIA[36] requirements around privacy, no response data were shared with the University or any other parties to ensure that the respondent's information remained private.

Biographical questions in the supervision instrument included their highest qualification, whether they were themselves studying towards a doctoral degree (if they indicated that they had obtained a lower qualification), their national or provincial residency, supervision load, supervision capacity, and the college[37] through which they primarily supervise students. Supervisors were asked how students were typically allocated, and their typical method of communicating with students over procedural matters. Finally, supervisors were asked to indicate their perceived ability to attend to all their students and their perceived flexibility in changing their supervision styles to fit their students' needs.

The biographic questions added for students included their highest qualification, whether they were currently enrolled for a master's and doctoral qualification, and their perceived qualification progress. Additional information was included about their national or provincial residency and employment status, available funding for their studies, and the amount of time they estimated that they were able to spend on their studies per week. In addition to the way in which their supervisor(s) were allocated, within which college they were registered, their typical communication method with their supervisor, and whether they changed supervisors during their studies, was asked as part of the questionnaire.

Available institutional data provided access to student and supervisor data that may not have been readily available. The qualification data of students' studies, such as the qualification code, qualification credits and minimum time, formal degree type, initial registration date, current registration status, completion status and completion dates, were requested from the available institutional database, in addition to the necessary information that was required to link students with their supervisors.

Students' time to completion (for those who had graduated) was calculated from the available institutional data. Consistent with the previously discussed literature, students'

[36] The POPIA is the South African legislation that presides over privacy and data protection, similar to the European General Data Protection Regulation (GDPR)
[37] Within Unisa colleges represent different faculties.

completion time was calculated in months, as a more accurate representation of time spent on qualifications (Agné & Mörkenstam, 2018; Watson, 2008). These calculations were made between the students' first registration date and the results date for their dissertation or thesis. The registration date signifies the start of a student's academic journey, whereas the results date provides the formal prelude to signalling qualification completion. Since the dissertation and thesis are typically completed after coursework or other course requirements, the results date was assumed to represent a more accurate completion time. This also allowed for calculating time to completion in months, rather than only in full years (see section 2.3). The graduation date was not used in these calculations, since some processes involved are outside the control of supervisors and students (Agné & Mörkenstam, 2018; Geven et al., 2018; Palmer, 2016; Wamala & Oonyu, 2012; Watson, 2008).

To account for the underlying assumption on completion times for master's and doctoral students, each qualification minimum time was subtracted from the calculated time to completion (Palmer, 2016). This transformation allowed master's and doctoral time to completion to be comparable, where minimum time would be represented by zero (0) months (thus 12 months for master's and 24 months for doctoral students). Given that the number of respondents who could form student-supervisor dyads was relatively small for those who completed their studies, this additional transformation meant that master's and doctoral records could be pooled in order to increase the power of the analysis.

After the time to completion was calculated, instances where students completed their qualifications in less than the minimum time, were interpreted as incorrect records (Van Lill, 2019). For instance, students were registered for extended periods, and the qualification name and code had changed. Their later registrations under the newer qualification names recorded their first year in the new qualification code as the start of the new qualification, rather than their first year of registration in a master's or doctoral degree. Where it was possible to identify such records, the initial registration date was used. Alternatively, the records were removed.

4.8. Data analysis

The data collection method described above provided three distinct data sources used in this project. Data sourced via the online survey platform provided two data files, one specifically containing the responses from students and the second containing responses from supervisors. The third data source included institutional data concerning students and supervisors, and contained the required information to link student and supervisor records. The following section provides an overview of how the abovementioned data was analysed so as to best answer the research questions. The analytical process includes a brief description of the analysis platform, the data cleaning process and underlying statistical assumptions, in addition to reporting on the descriptive data analysis methods. Thereafter, the process followed to investigate the validity and reliability of the research instrument is defined. The section concludes with a description of the inferential statistics that offer evidence for answering the research question.

The data for this study were analysed with R, version 4.0.3 (2020-10-10) “Bunny-Wunnies Freak Out” (R Core Team, 2020), in the RStudio Integrated Development Environment (IDE), Version 1.4.1717 “Juliet Rose” (RStudio Team, 2021). R is an open-source software environment that allows for advanced statistical analysis and graphical data presentation. The base package of R provides the programme’s foundation in addition to some basic operations. However, additional packages or libraries are required to use more advanced statistical processes (Field et al., 2012). The specific libraries loaded in this study are summarised in Appendix C: Table 72 R Libraries applied. RStudio is a commercial programming platform that assists in utilising R and is available for free for educational purposes (RStudio Team, 2021).

4.8.1. Data cleaning and statistical assumptions

The data must be screened before the analysis to accurately interpret statistical data (Zygmont & Smith, 2014). This process involves the data cleaning stages to correct detectable mistakes, the treatment of missing values (Moritz & Bartz-Beielstein, 2017; Zygmont & Smith, 2014), and the distribution assumptions that underpin multivariate analysis (Zygmont & Smith, 2014).

Descriptive statistical methods were employed in order to assist in the initial screening and the later description of variables. Descriptive statistical methods provided a method of summarising and inspecting the response distributions of the sample on a range of variables. This study used frequencies and measures of central tendency, or dispersion, to explore and describe the data and ensure consistency with the analytical assumptions (De Vos et al., 2011).

One such assumption is that the data is free of missing values or outliers (Hair et al., 2014; Moritz & Bartz-Beielstein, 2017). Within the current study, outliers in the self-report instruments were of little concern due to the reliance on Likert-type scales (Rui Sarmento & Costa, 2019). However, several respondents did not provide answers to all the questions, resulting in missing values. Solutions typically employed to remedy missing values are: to exclude the response from a particular analysis (Hair et al., 2014; Zygmont & Smith, 2014); or to replace the value with a possible alternative (Hair et al., 2014; Moritz & Bartz-Beielstein, 2017). During data exploration, 160 student respondents were found to have missing data on the Likert-type scales, 130 had a single missing value, and 30 respondents had two missing values. In the supervisor dataset, 24 had missing values, 16 missed a single response, seven missed two responses, and one respondent missed three of the Likert-type questions. No specific pattern seemed evident for the distribution of missing values. As such, the missing data was presumably linked to the particular respondents (i.e., refusal to respond or indifference). There were also very few missing values that did not seem to be a source of bias in the data. As discussed by Hair et al. (2014), missing data can be considered low if it contains under ten percent of an individual observation. Due to the low number of missing data, instances of missing data were explicitly treated as indifference, and thus imputed with the scale mid-point (i.e. 4) (Rui Sarmento & Costa, 2019; Zygmont & Smith, 2014).

Responses to the Likert questions were further investigated to ensure variability in the choice options. So as to avoid including respondent's data where only a single number was selected, the standard deviations were calculated for each respondent's answers to the Likert questions. Standard deviations below 0.5 were considered for removal. Overall, student respondents (n = 1 323) standard deviation ranged between 0.53 and 3.03. The initial Supervisor respondents (n = 181) included one respondent who only selected the number five as a response option (SD = 0). Once removed, the remainder of the respondents (n = 180) reflected standard deviations between 0.93 and 2.81.

The statistical measures employed in this study were based on the general linear model, which meant that the data needed to adhere to several assumptions for the analysis to be valid. These assumptions included linearity, normality, homoscedasticity, and independence (Hair et al., 2014).

Linearity meant that if a relationship was present between two variables, that the value of one variable needed to increase or decrease in linear relation to the other. Whereas, if a nonlinear relationship were present, these statistical measures would not be able to detect it (Hair et al., 2014).

Similarly, if the data deviates too far from a **normal distribution** curve, the resulting tests may be considered invalid (Cain et al., 2017; Field et al., 2012; Hair et al., 2014). However, some techniques are robust against normality violations, and large sample sizes tend to diminish the effects of non-normal data distributions. The guideline for these measures includes that for samples larger than 200, deviations from normality may be negligible (Hair et al., 2014). Normality is investigated by calculating the skewness and kurtosis of a response distribution. In this instance, skewness of 1.5 and kurtosis of 3 or lower would indicate a normal univariate distribution when samples exceeded 200 (Awang, 2012). Alternatively, skewness exceeding two and kurtosis exceeding seven can be considered a deviation from normality, where factor analysis techniques are applied, as discussed later (Zygmont & Smith, 2014). The Shapiro-Wilk test for univariant data, and the Mardia measurement for multivariant data, are statistical measures that explore the normality assumptions of the data. However, both measures tend to be oversensitive to large sample sizes, and may show statistical significance for negligible differences (Cain et al., 2017; Field et al., 2012; Zygmont & Smith, 2014). To offset this limitation, QQ-plots were drawn in order to visualise what the data for composite scores would look like if it were normally distributed against the actual data distribution (Field et al., 2012). Realistically, no dataset would be perfect, and as described by Yang and Liang (2013, p. 62): “In applied studies, the observed data often present some degree of non-normality”.

Homoscedasticity assumes that the dependent variable has an equal variance between the different independent variables. Levene's test was used during comparisons using inferential statistics to investigate homoscedasticity in the variables. Although it should be noted that the Levene test also becomes oversensitive when used with large samples (Field et al., 2012; Hair et al., 2014). Finally, the data is assumed to be **independent**, where one respondent's responses do not influence those of another (Field et al., 2012; Hair et al., 2014).

Inferential statistical tests refer to statistical significance in order to highlight if notable differences or similarities are detected between variables. Statistical significance refers to the probability that a particular finding may have resulted from random chance rather than imply a difference in the population (Field et al., 2012). Significance levels within the social sciences, also referred to as the p-value, are typically accepted when $p < .05$; or for more rigorous tests, where $p < .01$ may be proposed (Field et al., 2012). Larger sample sizes increase the statistical power of the analysis (Hair et al., 2014). Whereas statistical power refers to the ability of a statistical measure to detect a significant difference. If there is too much statistical power (typically large samples), almost any difference would be considered significant, and the test would be oversensitive (type I error). If there is too little statistical power (typically with small samples), even large differences would not be considered to be statistically significant, and the test would be insensitive (type II error) (Hair et al., 2014). As a result, effect sizes have become useful measures to provide a means of comparison for inferential statistics.

The **effect size** of a statistical test provides a standardised comparable metric to indicate the size of the measured effect. The metric provides a means by which to determine the 'meaningfulness' of a possible difference or similarity, which provides additional information to judge the statistical significance (Cohen, 1988; Hair et al., 2014). A large effect size would be more likely to be detected than a smaller effect size. Furthermore, the effect sizes of correlations are equal to the actual correlations between variables (Hair et al., 2014). Effect sizes are interpreted according to typically promoted thresholds, which are usually based on the work of Cohen (1988).

4.8.2. Measurement validation

Two critical aspects of a measurement are the validity and reliability of the measured constructs. Overall, validity refers to how accurately the measurement represents the underlying constructs (Awang, 2012; De Vos et al., 2011; Hair et al., 2014), whereas reliability refers to the extent to which a measure can be determined to be free of error, or the degree to which it remains consistent (Hair et al., 2014). Factor analysis was used in this study to investigate different elements of the measurement validity, whereas the constructs' reliability was investigated with other statistical measures (Awang, 2012).

Due to practical and theoretical considerations, only the instrument for students was analysed in the validity investigation. Practical considerations centred around the sample size requirements of factor analysis techniques are discussed below. As discussed in previous chapters, the theoretical considerations centred around the idea that students' experiences relate to their academic performance. A similar argument was made by Al-Muallem et al. (2016) in their investigation of the perspectives of research supervisors' readiness and needs. From the outset, it is necessary to acknowledge that the factors or constructs identified in this analysis may differ between students and supervisors. Students and supervisors tend to rate questions asking about their experiences differently (Fleming et al., 2013), and have different perspectives regarding their supervision relationships (Al-Muallem et al., 2016; Ali et al., 2016; Orellana et al., 2016). Although such differences do not necessarily translate into a different factor structure, the possibility must be acknowledged. The comparison between the measured scores of students and supervisors in the data analysis chapter nonetheless provides useful information concerning support and communication in their supervision relationships (Sampson et al., 2016).

Factor analysis refers to a group of statistical measures that can investigate the presence of a smaller number of latent constructs by examining correlations or covariations between variables (Schreiber et al., 2006). Spearman initially used factor analysis methods to investigate the structure of intelligence in 1904 (Zygmont & Smith, 2014). This form of analysis assists in summarising the interval or quasi-interval data, such as Likert items (Makhubela & Mashegoane, 2019), so as to ensure that the data remains interpretable and use the latent variables as proxies for the underlying conceptual constructs in further analysis (Yong & Pearce, 2013). This approach requires factor analysis techniques to depend heavily on a theoretical or conceptual foundation for interpreting the latent variables (Hair et al., 2014). The theoretical focus is critical, because a factor analysis approach provides a statistical estimate of the data, regardless of whether the estimated models make sense theoretically or practically, and as such, substantial interpretation is needed so as to ensure that a structure is utilised in research that makes sense (Hooper et al., 2008).

There are two main factor analysis approaches, notably confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) (Schreiber et al., 2006; Yong & Pearce, 2013). Both approaches are linear (Rui Sarmento & Costa, 2019) and assist in reducing the number of variables in the analysis. However, these techniques investigate the possibility of latent variables from different perspectives. The CFA approach serves to provide evidence for a set of hypothesised construct or group of variables, requiring the researcher to specify relationships upfront (Hair et al., 2014; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013). The EFA approach uncovers latent patterns without an a priori conceptualisation of possible constructs, where variables share common variance, allowing the researcher to explore relationships that may not have previously been considered (Hair et al., 2014; Orcan, 2018; Yong & Pearce, 2013). Both approaches provide information about underlying variables that are not measured directly; however, the combination of the variables may be used to represent the identified construct (Yong & Pearce, 2013).

The instrument validation discussion for this study will follow the outline Awang (2012) presented. Awang (2012) describes assessing several aspects of validity (and reliability) through a factor analysis approach. This outline thus assists in providing a structure for discussing the findings in the CFA and EFA used to validate the research instrument.

The types of validity considered are: content validity, face validity, and construct validity (Awang, 2012). Content validity is characterised by the overall representativeness of a particular construct to ensure those critical elements form part of the measurement tool. Face validity means that respondents can reconcile the purpose of the study with the questions being asked (De Vos et al., 2011). Both types of validity are more subjective, and require researchers to judge the adequacy of the information (De Vos et al., 2011; Hair et al., 2014). Construct validity, on the other hand, can be demonstrated through factor analysis techniques (Awang, 2012) and reflects the typical interpretation of validity (whether the instrument measures what it claims to) (De Vos et al., 2011; Hair et al., 2014; Makhubela & Mashegoane, 2019), particularly if the instrument is consistent with the theoretical perspective (Hair et al., 2014; Makhubela & Mashegoane, 2019).

Construct validity can further be divided into investigations of convergent and discriminant validity (De Vos et al., 2011). Convergent validity is attained when items that are theoretically supposed to load highly on a construct converge, which is presented through the item's unidimensionality (Awang, 2012; De Vos et al., 2011; Hair et al., 2014).

Unidimensionality ensures that all items related to a single concept obtain sufficient factor loadings on their respective constructs, while items with low loadings are removed (Awang, 2012; Hair et al., 2014). The interpretation in this process is that the latent variable can sufficiently explain the associated item variables, and that each item relates to only a single construct (Hair et al., 2014; Likert, 1932). According to Awang (2012), items with low loadings ought to be removed individually, starting with the lowest values. Items with lower loadings may be retained based on additional statistical and theoretical evidence. Convergent validity is additionally established through the Average Variance Extracted (AVE), which can be calculated from the standardised loadings of a CFA. For a construct to attain convergent validity, an AVE of 0.5 or higher needs to be presented (Awang, 2012; Hair et al., 2014).

In contrast, discriminant validity (or divergent validity) is indicated when items do not load on factors or constructs that they are not related to theoretically (De Vos et al., 2011; Hair et al., 2014; Rui Sarmento & Costa, 2019). Potential problems with the discriminant validity of an item could be displayed through a high Modification Index (MI) value in a CFA, where multiple high MI values may indicate that an item could be removed. In order to maintain discriminant validity, correlations with other constructs should not exceed 0.85 (Awang, 2012). Alternatively, to investigate the discriminant validity in a CFA, the squared construct correlations of two latent variables are compared with the AVE of a construct, where a higher AVE would provide evidence of discriminant validity (Hair et al., 2014).

The choice of whether to use CFA or EFA to explore or validate a particular instrument depends on the research needs (Zygmont & Smith, 2014). For the current study, the research instruments were based on an existing theoretical framework. As such, a CFA was used first to test the hypothetical structure of the instrument (Orcan, 2018; Rui Sarmento & Costa, 2019). Due to the study's exploratory nature, alternative structures were investigated through a combination of EFA and CFA (Orcan, 2018; Rui Sarmento & Costa, 2019). In this instance, the EFA was used to suggest an alternative factor structure and assist in building new constructs, and the CFA was used to test whether the new structure presented a superior alternative for this study and formally validate the measurement model (Hair et al., 2014; Orcan, 2018; Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013).

In the instance where the alternative factor structures were explored, the dataset was split into a training (EFA) and testing or validating (CFA) dataset, consistent with best practices (Hair et al., 2014; Orcan, 2018). This meant that the exploratory and confirmatory analysis was based on independent samples, increasing the quality of analysis. Splitting the data was also possible, given the size of the student sample, to ensure enough observations were included for each part of the investigation (Hair et al., 2014; Orcan, 2018; Schreiber et al., 2006).

It is typically agreed in the literature that factor analysis techniques require large sample sizes to reduce the measured error (Yong & Pearce, 2013) and provide reliable results (Schreiber et al., 2006). However, there is typically a lack of consensus over the minimum required respondents, leading to various guidelines on the number of respondents required for these techniques. These guidelines may suggest estimates based on arbitrary numbers, such as at least 300 (Field et al., 2012; Yong & Pearce, 2013) or 400 respondents (Pituch & Stevens, 2016). Alternatively, sample size estimates may be based on common rules of thumb related to the number of variables included, such as needing five to ten respondents for every question item (Field et al., 2012; Hair et al., 2014; Makhubela & Mashegoane, 2019; Schreiber et al., 2006; Yong & Pearce, 2013;

Zygmont & Smith, 2014) but may be as large as 30 respondents per variable (Yong & Pearce, 2013). Applying the estimate of ten respondents per variable suggests that the analysis needed more than 510 respondents in order to consider the validity of the factor structures that included the 51 Likert-type questions. The large number of respondents in this study meant that there were enough observations in the data, and that the data could be split for the exploratory analysis.

The above description provides an overview of how the validity of the research instruments was evaluated. However, the CFA and EFA have unique considerations, which will briefly be outlined below. This will clarify assumptions made during each approach in exploring the measurement item structures.

4.8.2.1. Confirmatory factor analysis

CFA estimates how well a proposed data structure fits a particular dataset during instrument validation (Zygmont & Smith, 2014). The analysis allows inferences to be made on how well the observed variables measure a particular construct (Hair et al., 2014). The structure needs to be hypothesised, typically based on empirical data (through an EFA) or a theoretical framework. At the same time, the model utilises the covariance matrix structure within the data to estimate the model fit (Hair et al., 2014; Hooper et al., 2008; Makhubela & Mashegoane, 2019; Schreiber et al., 2006). CFA analysis is based on several assumptions made in multivariate analysis. These assumptions include multivariate normality that the data utilised in the analysis has been cleaned (free of missing data and outliers) (Rui Sarmento & Costa, 2019), as well as that each construct preferably contains more than three items or variables (Pituch & Stevens, 2016).

The CFA in this study was conducted through the Lavaan Library in R, utilising the Maximum Likelihood estimation (ML). The ML is somewhat robust against violations of normality (Jackson et al., 2009; Yang & Liang, 2013). The analysis used the Wishart ML estimator, which utilises the unbiased sample covariance matrix as the basis of the analysis, providing comparable results to model estimates conducted in other structural equation modelling software (EQS, LISREL, and AMOS) (Rosseel, 2020). The resulting

CFA outputs were interpreted by examining the model fit indices, the standardised parameter estimates, and the modification indices (Rui Sarmento & Costa, 2019).

In assisting with interpreting CFA models, standard graphical presentations of interactions (Path diagrams) are typically included to illustrate the investigated data structure (Rui Sarmento & Costa, 2019). Path diagrammes were created, which represent latent variables as circles, and representing variables with square boxes (Figure 12). Direct effects are displayed in single arrows between the variables and particular latent constructs, while unexplained correlations are displayed as double arrow lines, typically between latent constructs (Hair et al., 2014; Rosseel, 2012; Schreiber et al., 2006). Variable error is sometimes also visualised to provide additional information within the model (Schreiber et al., 2006).

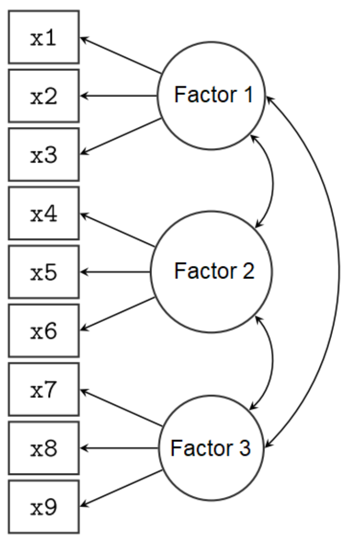


Figure 12: Example of a Path Diagramme adapted from Rosseel (2012, p. 8)

The model fit indices assist in evaluating whether or not the overall performance of the CFA model is acceptable (Awang, 2012; Moss, 2016). There are several articles and guides on selecting appropriate fit indices and thresholds. However, there is not much consensus on which indices to include (Awang, 2012; Jackson et al., 2009; Makhubela &

Mashegoane, 2019). Many of the fit indices are based on the Chi-square value, which compares the difference between the predicted model covariance matrix with the observed covariance matrix (Hooper et al., 2008; Moss, 2016; Rui Sarmento & Costa, 2019). Although there is an agreement that the Chi-square p-value should not be significant at the selected cut-off (typically $p < 0.05$) (Awang, 2012; Hair et al., 2014; Hooper et al., 2008), it has been recognised that large samples would result in significant values, regardless of fit (Hair et al., 2014; Hooper et al., 2008). Thus, a combination of indices is typically considered (Makhubela & Mashegoane, 2019; Schreiber et al., 2006). Model fit indices can be classified into three overarching categories (i.e. Absolute fit, Incremental fit, and Parsimonious fit) (Awang, 2012; Makhubela & Mashegoane, 2019), where it is typical to report indices from each category (Awang, 2012). For this study, several indices are reported, due to their wide application and familiarity in the literature. The fit statistics and thresholds are reported below (Table 15). Bolded thresholds were specifically applied for this study. It ought to be noted that dogmatic adherence to index thresholds is discouraged, as this may result in rejecting an otherwise acceptable model, reiterating that the theoretical framework must be consulted when conducting a CFA (Hooper et al., 2008; Makhubela & Mashegoane, 2019).

Table 15: Fit indices

Index[38]	Category	Level of Acceptance	Level of Acceptance	Source
Chi-Square	Absolute fit	**Standard**	**P > 0.05 ***	(Awang, 2012; Hair et al., 2014; Hooper et al., 2008; Moss, 2016)
Chisq / df	Absolute fit	**Very good**	**≤ 1**	(Rui Sarmento & Costa, 2019)
		Good	**≤ 1.5**	(Makhubela & Mashegoane, 2019)
			1-2	(Rui Sarmento & Costa, 2019)
		Mediocre	**2-3**	(Moss, 2016; Schreiber et al., 2006) (Awang, 2012)
			2-5	(Moss, 2016; Rui Sarmento & Costa, 2019)
		Bad	> 5	(Rui Sarmento & Costa, 2019)

[38] RMSEA (Root Mean Square Error of Approximation); SRMR (Standardised Root Mean Square Residual); CFI (Comparative Fit Index); NFI (Normed Fit Index); AFGI (Adjusted Goodness of Fit Index); AIC (Akaike Information Criterion).

Index[38]	Category	Level of Acceptance	Level of Acceptance	Source
RMSEA	Absolute fit	**Very good**	**< 0.05**	(Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019)
		Good	**0.05 - 0.08**	(Awang, 2012; Hair et al., 2014; Hooper et al., 2008; Makhubela & Mashegoane, 2019; Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019; Schreiber et al., 2006)
		Mediocre	0.08 - 0.10	(Rui Sarmento & Costa, 2019)
		Unacceptable	> 0.10	(Rui Sarmento & Costa, 2019)
SRMR	Absolute fit	**Perfect**	**0**	(Hooper et al., 2008; Pituch & Stevens, 2016)
		Good	**< 0.05**	(Hooper et al., 2008; Pituch & Stevens, 2016)
		Acceptable	≤ 0.08	(Hair et al., 2014; Hooper et al., 2008)
			0.05 – 0.10	(Pituch & Stevens, 2016)
CFI	Incremental fit	**Very good**	**> 0.95**	(Hooper et al., 2008; Makhubela & Mashegoane, 2019; Rui Sarmento & Costa, 2019; Schreiber et al., 2006)
		Good	**0.9 - 0.95**	(Awang, 2012; Hair et al., 2014; Hooper et al., 2008; Moss, 2016; Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019)
		Mediocre	0.8 - 0.9	(Rui Sarmento & Costa, 2019)
		Bad	< 0.8	(Rui Sarmento & Costa, 2019)
NFI	Incremental fit	**Very good**	**> 0.95**	(Rui Sarmento & Costa, 2019; Schreiber et al., 2006)
		Good	**0.9 - 0.95**	(Awang, 2012; Makhubela & Mashegoane, 2019; Moss, 2016; Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019)
		Mediocre	0.8 - 0.9	(Rui Sarmento & Costa, 2019)
		Bad	< 0.8	(Rui Sarmento & Costa, 2019)
AFGI	Parsimony Fit	**Standard**	**AFGI > 0.90**	(Awang, 2012; Hooper et al., 2008; Pituch & Stevens, 2016)
		Standard	AFGI ≥ 0.95	(Schreiber et al., 2006)
AIC		**The index used as a comparison between models**	**Lower than the baseline value indicates a better fit.**	(Hooper et al., 2008; Makhubela & Mashegoane, 2019; Schreiber et al., 2006)

* Significance expected in larger samples

The standardised parameter estimates were inspected in order to judge the appropriateness of variables. Parameter estimates needed acceptable loadings on a latent factor to provide evidence of unidimensionality (Awang, 2012; Hair et al., 2014). Standardised loadings are typically considered acceptable at 0.5 or more, and are useful for newly developed instruments (Awang, 2012; Hair et al., 2014). Where standardised loadings below 0.5 are considered for possible deletion. This process formed an iterative approach, removing the lowest values first, until acceptable fit and loading levels were reached (Awang, 2012). According to Awang (2012), it is possible to keep items that do not have acceptable loadings if the model fit indices are acceptable. However, loadings below 0.4 were typically removed.

A final investigation was made of the Modification Indices (MI) once the model fit and parameter estimates had been considered (Schreiber et al., 2006). The MI provided calculations of all the possible relationships that were not included in the model hypothesis, thereby acting as a diagnostic procedure for a particular model (Hair et al., 2014). These calculations provided insight into possible relationships between items within constructs, and cross-loadings between items and different constructs (Hair et al., 2014). If relationships were evident, it was possible to account for them within the CFA model by including a covariance between the error terms of items, typically resulting in improved fit (Hair et al., 2014; Hooper et al., 2008; Makhubela & Mashegoane, 2019). It ought to be noted that although such model modifications improve model fit, the improvement would typically be superficial, and violate measurement assumptions (Hair et al., 2014; Hooper et al., 2008). Thus, cross-loadings should not be included in model adaptions based on MI calculations; however, these may provide insight into possible problematic items that could be removed. Modifications must be theoretically appropriate (Hair et al., 2014; Hooper et al., 2008; Schreiber et al., 2006). Models that include such modifications are also considered exploratory (Schreiber et al., 2006), which is consistent with the purposes of the study. Because MI adaptions were made in the validation, it would only be possible to generalise if similar evidence and model fit is found across different samples and contexts (Hair et al., 2014).

Finally, constructs preferably need to contain at least three items. Although it is possible to retain fewer variables, this is not advised. As a result, one needs to balance several criteria, mainly between acceptable model fit and the inclusion of enough indicators to represent the construct (Hair et al., 2014). For the project, items were only removed if necessary. All attempts were made to ensure that items remained within the measurement whilst attaining the desired fit levels and factor loadings.

Although the CFA approach indicated promising results, the study also utilised an EFA approach for further investigation. Due to theoretical considerations across the multiple models, and the exploratory nature of including MI changes in the project (Schreiber et al., 2006), the EFA allowed alternative factor structures to be evaluated. The following section thus expands on how the EFA was conducted for this study.

4.8.2.2. Exploratory factor analysis

The EFA is an exploratory approach used to consider possible latent dimensions (also called components or factors) by investigating relationships between variables in a dataset (Hair et al., 2014; Zygmont & Smith, 2014). The approach does not presuppose a structure of possible relationships; as a result, the number of possible latent factors are unknown before the analysis, and discovered as the approach combines highly correlated variables. The exercise aims to find the fewest number of latent factors that provide the best description of the data (Hair et al., 2014; Yong & Pearce, 2013). Identified factors represent concepts that may not be directly measurable (Field et al., 2012), and also acts to summarise or condense the set of variables for further analysis (Hair et al., 2014). Towards this end, the principal axis factoring approach was used, because the latent variables are considered generalisable beyond the measurement instrument (Hair et al., 2014; Zygmont & Smith, 2014).

It is important to reiterate that theoretical considerations must also guide an EFA analysis. The analysis procedure will produce factors regardless of the quality of the data (Hair et al., 2014; Pituch & Stevens, 2016). Where it was noted that “Factor analysis is always a potential candidate for the “garbage in, garbage out” phenomenon” (Hair et al., 2014, p. 97). Furthermore, theoretical interpretations of an EFA need to be supported by the data

(Zygmont & Smith, 2014), avoiding scenarios where simply anything becomes acceptable.

EFA uses observed correlations between variables and thus assumes that the relationships between variables are linear (Pituch & Stevens, 2016), displaying both univariate and multivariate normality; and that there are no extreme outliers in the data (Field et al., 2012; Hair et al., 2014; Yong & Pearce, 2013). However, EFA can be used if the data violates the multivariate assumption of normality (Yong & Pearce, 2013), where some evidence of multicollinearity needs to be evident in the data (moderate correlations) (Zygmont & Smith, 2014). The EFA was conducted in R, specifically utilising the minimal residuals (MINRES) algorithm, which was shown to be robust against possible violations of distribution assumptions (Zygmont & Smith, 2014).

As noted previously, the data used in the exploratory analysis was split. A randomly selected subsample of data was used in the EFA as a training dataset (n = 595). After the EFA analysis was conducted, each structure was tested through a CFA analysis as described above, with the remaining subsample (n = 728) to check the proposed factor analysis structures.

The Kaiser-Meyer-Olkin (KMO) measure was used to check the sampling adequacy in the EFA (Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014). The technique is often used as a first step in the analysis approach when conducting EFA and investigates each variable's overall sampling adequacy (Rui Sarmento & Costa, 2019; Yong & Pearce, 2013). For this analysis approach, KMO scores above 0.5 were acceptable (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014). Where values were below 0.5, problematic variables were first removed (Hair et al., 2014; Yong & Pearce, 2013).

Bartlett's test of sphericity was used as a diagnostic test that compared the correlation matrix of the data to an identity matrix (where no relationships are found between variables). Significant differences ($p < .05$), as measured by Bartlett's test, signify that the correlation matrix differs significantly from an identity matrix (Field et al., 2012; Hair et al., 2014; Yong & Pearce, 2013; Zygmont & Smith, 2014). It should be noted that similar to other tests of significance, Bartlett's test is sensitive to sample size (Hair et al., 2014).

Although some correlations are expected and desired, multicollinearity (very strong or perfectly correlated variables) can still be problematic for EFA analysis. The Determinant score can indicate an absence of multicollinearity (Field et al., 2012; Kyriazos, 2018; Yong & Pearce, 2013). Generally, the Determinant score should be above 0.00001 (Field et al., 2012; Yong & Pearce, 2013).

The number of factors that need to be extracted in utilising the EFA approach must be specified. Due to the exploratory nature of the analysis, it is not always possible to know the number of factors to be extracted. Several methods have been developed to determine the number of factors; however, such approaches do not typically agree on the number of factors in an analysis (Zygmont & Smith, 2014). Popular methods include the number of factors with an eigenvalue higher than one (Hair et al., 2014; Rui Sarmento & Costa, 2019; Zygmont & Smith, 2014), retaining all the factors that, in combination, explain a certain threshold of variance extracted (Hair et al., 2014; Rui Sarmento & Costa, 2019), or investigating the scree plot as a more subjective approach (Hair et al., 2014; Pituch & Stevens, 2016; Rui Sarmento & Costa, 2019; Zygmont & Smith, 2014). More recently, parallel analysis has been used to determine the number of factors, heralded as a more accurate approach to estimating the number of factors needed (Pituch & Stevens, 2016; Zygmont & Smith, 2014). Although parallel analysis may overestimate the number of factors needed (Pituch & Stevens, 2016). It is important for the factors to also make sense theoretically, where the meaningfulness of the constructs is crucial in deciding how many to retain (Hair et al., 2014; Makhubela & Mashegoane, 2019; Pituch & Stevens, 2016; Zygmont & Smith, 2014). Typically, multiple factor-structures are examined and compared in order to arrive at a solution that best represents the data (Hair et al., 2014).

The abovementioned approaches were utilised within this study. However, the primary focus was to ensure that the factor loading represented a simple structure that was theoretically interpretable (Hair et al., 2014; Makhubela & Mashegoane, 2019; Yong & Pearce, 2013). A simple structure for an EFA would result in variables that only load highly on a single factor, with minimal cross-loadings (unidimensionality), which can be theoretically interpreted as latent constructs, as well as to ensure that three or more variables load strongly on each construct (Makhubela & Mashegoane, 2019; Yong & Pearce, 2013).

It is also possible to create model fit statistics to evaluate a particular factor structure (Zygmont & Smith, 2014). Field et al. (2012) provided a process for calculating the RMSR for a specific factor structure, arguing that the proportion of residuals ought to be lower than 0.05. Some of the fit statistics are automatically calculated in R. Due to the exploratory nature of the analysis and the additional use of CFA, these were not extensively considered in this study. However, calculations are available in the analysis outputs provided in the following chapter and the data tables within Appendix E.

Two aspects of the results need to be considered in order to create a simple structure. Firstly, the rotation method is applied to the analysis, and the second is the acceptable thresholds for factor loadings. The initial output of an EFA tends to be challenging to interpret. However, if a rotation is applied to the data, the underlying structures do not change, whereas the data becomes more interpretable (Field et al., 2012; Makhubela & Mashegoane, 2019; Pituch & Stevens, 2016; Yong & Pearce, 2013; Zygmont & Smith, 2014). Two types of rotations can be applied are orthogonal rotations (which assume that factors are not related to each other), and oblique rotations (which assume that factors can be correlated) (Field et al., 2012; Hair et al., 2014; Yong & Pearce, 2013; Zygmont & Smith, 2014). Orthogonal rotations (i.e. Varimax) simplify the interpretations of factor scores because they assume that the additional complication of factor correlations does not exist (Field et al., 2012; Yong & Pearce, 2013; Zygmont & Smith, 2014). This approach is consistent with Gatfield's conceptualisation of the relationship between Support and Structure on a 2X2 Cartesian plane (Gatfield, 2005). A critique against this approach in the social sciences is that factors are not likely to be unrelated, due to complex social relations, favouring the presumably more accurate oblique rotations (i.e. Direct Oblimin) (Field et al., 2012; Yong & Pearce, 2013; Zygmont & Smith, 2014). Choosing between rotation methods depends on the study's theoretical foundation (Field et al., 2012). However, some recommendations include using multiple rotation methods and comparing the final results (Zygmont & Smith, 2014). Given the exploratory nature of the analysis within this study, both rotations (Varimax and Direct Oblimin) were used. In utilising multiple methods, it is important not to select only the data that conforms to favourable interpretations (Zygmont & Smith, 2014). For this reason, Appendix E provides a more detailed outline of the analysis, so as to ensure transparency throughout the validation approach, discussed in depth in the following chapter.

When an EFA is conducted, all the variables are to some extent associated with all the extracted factors. Variables, however, need to load strongly enough on a particular factor to be considered part of the underlying construct (Hair et al., 2014; Yong & Pearce, 2013; Zygmont & Smith, 2014). Furthermore, the variables ought not to load strongly on more than one factor (cross-loading) (Yong & Pearce, 2013). There is, again, no consensus on how strongly variables need to load on the respective constructs. However, the literature suggests 0.32 (Pituch & Stevens, 2016; Yong & Pearce, 2013), or 0.3 - 0.4 as a bare minimum (Field et al., 2012; Hair et al., 2014; Makhubela & Mashegoane, 2019; Zygmont & Smith, 2014). Other authors consider loadings more than 0.4 (Field et al., 2012; Makhubela & Mashegoane, 2019; Pituch & Stevens, 2016) or 0.5 (Hair et al., 2014; Makhubela & Mashegoane, 2019; Pituch & Stevens, 2016). Factor loadings are typically also influenced by sample size, which suggests that with very large samples, much lower loadings may be accepted (Field et al., 2012; Yong & Pearce, 2013). In addition to the factor loadings, variable commonalities must be investigated. Communalities represent the amount of common variance shared among variables within the analysis. Higher common variance results in lower unique variance, or error. Variables with low communalities may also be removed from the analysis. Specific thresholds include communalities lower than 0.2 (Yong & Pearce, 2013), or 0.3 (Rui Sarmento & Costa, 2019), with some authors suggesting that communalities below 0.4 ought to be eliminated (Makhubela & Mashegoane, 2019).

The EFA process allows for many factor models (and the number of latent factors) that are technically comparable from a purely mathematical perspective (Zygmont & Smith, 2014). As described above, the approaches to conducting and evaluating an EFA assist in discerning between models, where ensuring that the solution also makes sense theoretically is critical. Thus, throughout the process of conducting an EFA, the variables that load highly on a single factor were read together so as to interpret the core concept measured within the factor (Hair et al., 2014; Zygmont & Smith, 2014). The naming of factors thus assists in linking the measurements to a theoretical explanation. However, some authors also explain it as closer to an art (Yong & Pearce, 2013; Zygmont & Smith, 2014).

4.8.2.3. Validity conclusion

To conclude the validity discussion, it is important to note the critique by Borsboom, Mellenbergh, and Van Heerden (2004). Borsboom et al. (2004) critiqued popular criteria of validity that are based on nomological networks, where validation initiatives are based less on whether measurements function as they are designed, than on “the empirical relations between test scores match theoretical relations in a nomological network” (Borsboom et al., 2004, p. 1061). Their critique stems from the position that validity should be examined from an ontological perspective, where one can only measure a construct if it exists. Such a construct would causally change the outcome of a measurement, rather than discover from analytical processes what the instrument measures (considering validity from within the realm of epistemology). Borsboom et al. (2004) argue that measurements should be designed with a particular goal in mind so as to ensure validity, placing a strong emphasis on the theoretical perspective and design process. The psychometric properties retain their usefulness, but much less focus within this approach. What is critical within their view is that a theoretical explanation can describe the results (i.e., explain response behaviours on an instrument that would lead to specific outcomes within the measurement). As a result, the analytical information used in typical validation processes cannot be the only consideration for the validity of an instrument. Where the authors view such results as useful, it is presumably impossible only to utilise such measures towards test validity (Borsboom et al., 2004). The current study takes a similar theoretical stance concerning supervision relationships, as Borsboom et al. (2004) described. However, the approach in this study may also fall short of expectations when considering the full extent of what is implied. Measurements regarding supervision relationships seemingly remain in their infancy (Ali et al., 2016). As such, the current project assists in expanding on the literature with such foci.

In summary, the instrument validation was investigated through a combination of techniques. A CFA was used in order to explore the fit of the predesigned structure of the questions. Published conventions of what would constitute a good fit were used to make value judgements and improve the included items. The data was split into a training and a testing dataset in order to explore possible alternative factor structures. The training was used in an EFA to investigate whether the data would load onto different factors using this approach. This analysis investigated a two, three, and four-factor model utilising orthogonal (Varimax) and oblique (Direct Oblimin) rotations. The Varimax rotation was considered as it is assumed by the theoretical approach that the constructs were not correlated. In contrast, the Direct Oblimin rotation was included due to social science research conventions and apparent relationships between the factors. Each of the resulting six models was tested through a CFA using the testing dataset to ensure that such approaches were viable.

4.8.2.4. Reliability

The reliability of a measure is typically linked to stability over time, suggesting that similar scores would be assigned to similar experiences (Awang, 2012; De Vos et al., 2011; Field et al., 2012). The internal consistency of measurement is typically investigated to make inferences about the measurement reliability (Hair et al., 2014). The assumption is that items within a construct should correlate highly with the same construct and are typically measured using Cronbach's alpha (Field et al., 2012; Hair et al., 2014). Estimates for the construct's Cronbach's alpha should preferably exceed 0.7 (Awang, 2012; Field et al., 2012; Hair et al., 2014; Rui Sarmento & Costa, 2019). Estimates could be lowered to 0.6 (particularly for exploratory research) (Hair et al., 2014; Rui Sarmento & Costa, 2019), but should not be below 0.5, indicating low reliability (Hair et al., 2014; Rui Sarmento & Costa, 2019). Cronbach's alpha is somewhat sensitive to the number of variables, where a large number of items in a construct could artificially increase the Cronbach's alpha score (Field et al., 2012; Hair et al., 2014).

An additional measure for reliability, mainly used in CFA studies, is a construct's composite reliability (CR) (Hair et al., 2014). Similar to a Cronbach's alpha score, the CR of a construct should preferably be higher than 0.6 if it is to indicate that composite reliability was achieved (Awang, 2012; Hair et al., 2014). The AVE measured should be higher than the CR, where the AVE also has to be higher than 0.5 (Rui Sarmento & Costa, 2019). Popular analytical programmes do not automatically calculate the AVE and CR of CFA models, and require calculations to be done manually. Gaskin (2019) provides a useful Excel-based tool that was utilised to automate calculations of the AVE and CR, where more than two latent factors were presumed.

4.8.3. Inferential statistics

After exploring validity and reliability, an appropriate model was selected, and indices were created by averaging the scales for each relevant construct. Inferential statistics were used to explore possible relationships and differences between the relevant variables, which cannot be directly observed (Field et al., 2012; Frey, 2018). Since it is rarely (if ever) possible to collect relevant information from everyone within a study population, statistical measures are used to estimate the possibility that such relationships or differences are not due to random error or measurement bias (Frey, 2018). Although obtaining data that conform to the required standards to make such inferences is rare in practice, it is useful in order to gain some estimation within collected data (Frey, 2018).

Inferential statistics is typically described as an overarching label for various statistical techniques (Frey, 2018), and is further subdivided into parametric and non-parametric statistics. Parametric statistics hold various assumptions about the data collected, including that the data is independent at the interval level, normally distributed, and that the variance is homogeneous[39] (Field et al., 2012). To adhere to the stated assumptions, the sample size of a study becomes a crucial question before parametric statistics can be applied (Field et al., 2012). On the other hand, non-parametric statistic play a similar role. However, they do not require the same assumptions within the data, most notably, the assumption for normality. Where non-parametric statistics are argued to be less powerful,

[39] See section 4.8.1. for a discussion of the data assumptions for normality and homogeneity of variance, as well as significance tests and effect sizes.

this allows for an analysis with small datasets and where data is not normally distributed (Field et al., 2012). Although these constitute different approaches, analytical techniques with similar functions are available within both the parametric and non-parametric statistical groupings. The most notable difference is that non-parametric tests do not use the raw data scores, but instead rank the data from low to high and use the rankings within the statistical comparisons (Field et al., 2012). Within this study, non-parametric statistics were preferred, given that the techniques do not require that the data be normally distributed. In addition, within some of the sections, the sample size was presumably too small to conform to the requirements for parametric statistics.

As stated above, non-parametric statistics provide an overall description of several analytical techniques. For this study, the Wilcoxon rank-sum test was used, where comparisons were made between two groups, and the Kruskal-Wallis test was used where there were more than two groups to compare. For both techniques, the data was explored so as to indicate where deviations from normality were found, and Levene's test was conducted to explore the homogeneity of the variance. Whereas the effect size 'r' (0.1 = small, 0.3 = medium, 0 .5 = large (Cohen, 1988; Pallant, 2011)) was calculated for the Wilcoxon rank-sum test, and 'η^2' (0.01 = small, 0.06 = medium, 0.14 = large (Cohen, 1988; Lakens, 2013; Pallant, 2011)) for the Kruskal-Wallis test (Field et al., 2012). Relationships were measured between continuous variables and the Spearman correlation, whereas the Pearson correlation was used where the data conformed to parametric assumptions (Field et al., 2012). The 'r' values for the correlations were interpreted similarly as per the criteria above.

4.9. Ethics

Ethical clearance for this project was obtained prior to the data collection from the following committees:

- Ethics Committee of the Department of Psychology - Reference: PERC-17062A (Appendix D)
- Unisa College of Human Sciences Research Ethics Committee – Reference: 2018 CHS 006 (Appendix D)

- Research Permission Sub-committee (RPSC) of the Senate Research, Innovation, Postgraduate Degrees and Commercialisation Committee (SRIPCC) – Reference: 2018_RPSC_023_AR (Appendix D)

Respondents were provided with an informed consent letter before their participation and required to consent before they could view or respond to the questions. Participation in this project was voluntary, and respondents could withdraw at any point in the study. Consistent with this requirement, response data was only used if the online survey was submitted, signalling the completion of the survey. Although identifiable information was collected, such data were removed once it was possible to anonymise the datasets (after linking student and staff records) so to ensure that respondents' identities remained confidential.

Other than the identifiable nature of the study, the collected data was not considered sensitive and would not have presented respondents with significant risk. Nonetheless, all the collected data is treated as confidential. As described above, the analysis used statistical techniques that aggregated the data. As such, the presented data has been anonymised. The abovementioned precautions were in line with the granted clearances and requirements from the Protection of Personal Information Act (POPIA).

Chapter 5: Instrument validation

The purpose of this chapter is to provide an overview of the process to investigate the validity and reliability of the instrument within the context of the study. This chapter thus addresses the first research question: “RQ 1: Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?” The instrument’s validity was investigated through factor analysis approaches (CFA and EFA), as described in the previous chapter. Descriptions of the instrument reliability were interpreted from CR and Cronbach’s alpha scores. Only the student data was utilised in the factor analysis methods, for two main reasons: practically, because enough data was collected; and theoretically, so as to investigate supervision relationships from the perspective of students. This may suggest that the instrument, which presumably measures Gatfield’s (2005) supervision style approaches of supervisors and students, would be tailored to students’ responses, and that alternative models may exist from different perspectives.

The previous chapter outlined the initial steps taken concerning data cleaning. Respondents that only selected a single option were removed, and where only a few missing values were found, the scale mid-point (4) was imputed. One aspect of the data assumptions that have thus far not been described was the normality of the Likert data. Both CFA and EFA approaches utilised within this study are reportedly robust against some violations of normality assumptions; however, it remains critical to discuss this assumption.

To report on the normality assumptions, both the skewness and kurtosis of each item and multivariate distributions are briefly reported. To ensure that comprehensive approaches are taken, Shapiro-Wilk test statistics are reported, although due to the size of the data, it is expected to test significant deviations from normality. Thus, cut-off scores and QQ-plots, as discussed in the previous chapter (see section 4.8.1), were considered in making judgements regarding the data. After investigating the response distribution, the factor analysis approaches are described.

The instrument was primarily designed from the theoretical perspective described by Gatfield (2005). As a result, CFA approaches are described first. The theoretical framework posits the existence of two overarching concepts, i.e., Structure and Support. The initial goal of this project was to measure these specific constructs. In facilitating an understanding of the two concepts, Gatfield (2005) posited six sub-themes[40] in order to describe the intricacies embedded in supervision. The instrument design for this project was based on these six sub-themes (Table 14). Thus, an inspection of a six-factor model, although not planned initially, could not be ignored. Since this is the first study where this instrument has been used, it was expected that neither baseline model would result in appropriate measurements. Both models were adapted through the iterative removal of items based on the criteria expanded on in the previous chapter (see section 4.8.2.1).

Following the results of the CFA, an EFA was used to investigate possible alternative factor structures. The data for the factor analysis approaches were split, where EFA on the first dataset suggested several possible factor structures, which were tested with a CFA, utilising the second dataset. The chapter concludes with a summary discussion of the EFA approaches and a justification for utilising the 'CFA Two-Factor Modified Model' in the study. The analysis process is graphically illustrated in (Figure 13).

[40] As previously indicated, the subcategories did not include Technical support, due to the role played within this sphere by the institutional support services.

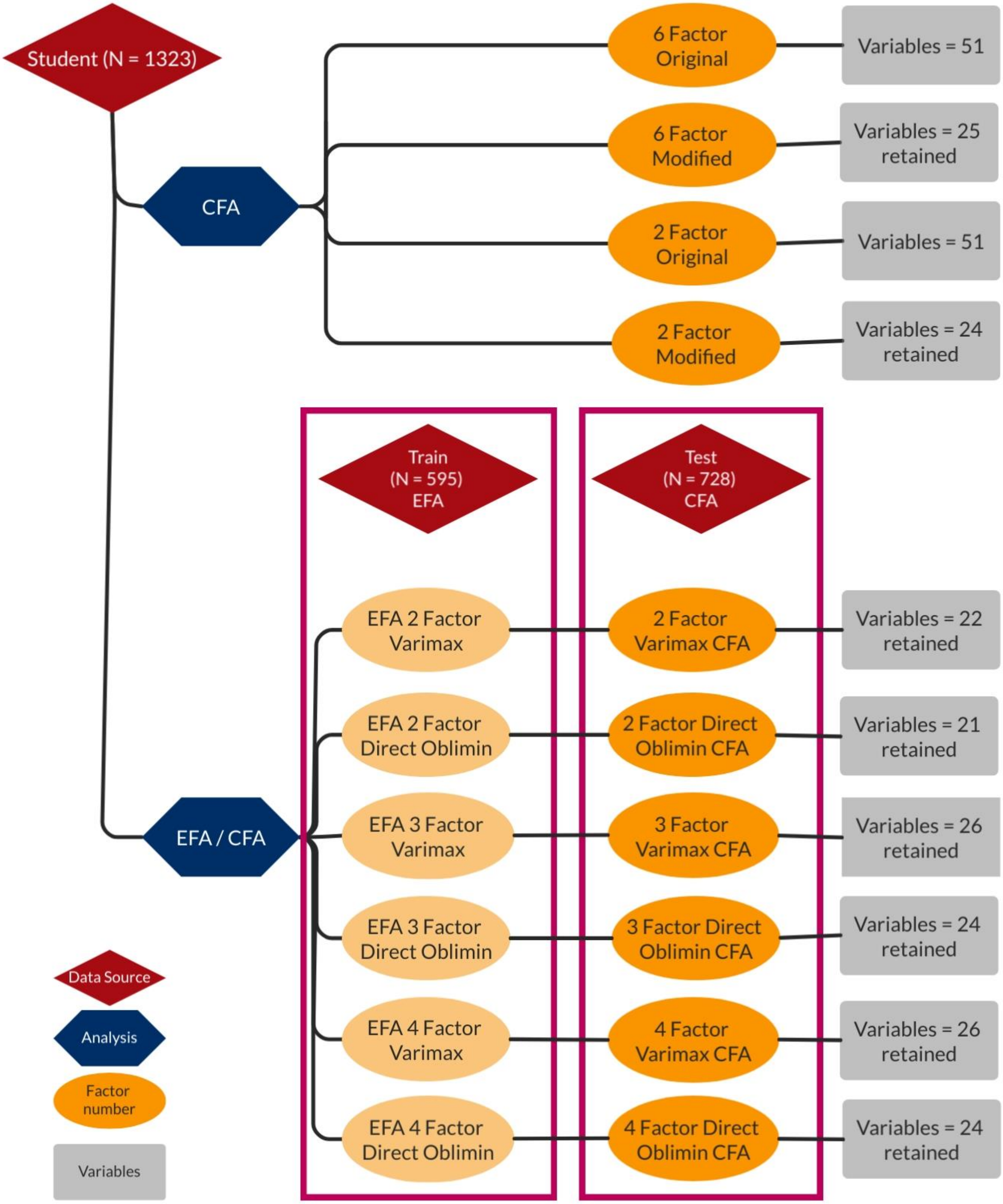


Figure 13: Validity – factor analysis overview

Source: Author (Visme)

5.1. Data description (normality assumption)

Descriptive statistics were utilised as the initial investigation of the Likert items. The data collected for both the supervisors and the students are described. A total of n = 1 323 completed unique student responses were recorded and used during the inspection of data structures. Mean scores of the seven-point scales ranged between M = 2.67 and M = 6.69, whereas 46 of the 51 items ranged between M = 3 and M = 6. Item standard deviations ranged between SD = 0.8 and SD = 2.2, whereas 45 of the items' SD scores ranged between 1.06 and 2.06. Respondents used the full range of response items within each variable (1 to 7). One of the items (Q_41) indicated large skewness (-4.06) and kurtosis (21.22). The remaining variables' skewness ranged between -1.82 and 0.95, whereas kurtosis ranged between -1.39 and 4.1. Except for Q_41, all items ranged between the cut-off thresholds, with skewness not exceeding 2, and kurtosis not exceeding 7 (Zygmont & Smith, 2014), which could be considered for removal (Table 16). Item Q_41 remained within the initial analysis. During the data exploration, the effects of removing this item at various stages were experimented with, and ultimately the item did not remain within the models to be discussed.

Table 16: Student Likert questions descriptive statistics

#	Item	n	X̄	sd	Mdn	min	max	skew	kurt	se
Q_01	Contractual arrangements	1 323	5.25	1.76	6	1	7	-0.77	-0.41	0.05
Q_02	Deadlines	1 323	5.25	1.73	6	1	7	-0.81	-0.24	0.05
Q_03	Established timeframes	1 323	5.56	1.54	6	1	7	-1.08	0.58	0.04
Q_04	Independence	1 323	4.46	1.99	5	1	7	-0.3	-1.12	0.05
Q_05	Staged write-up	1 323	5.01	1.73	5	1	7	-0.61	-0.56	0.05
Q_06	Standard of work (benchmark)	1 323	6.2	1.11	7	1	7	-1.82	4.1	0.03
Q_07	Supervisor turnaround time	1 323	4.19	2.06	4	1	7	-0.18	-1.25	0.06
Q_08	Timely feedback	1 323	5.93	1.29	6	1	7	-1.4	1.86	0.04
Q_09	Work independently	1 323	4.07	1.88	4	1	7	-0.11	-1.07	0.05
Q_10	Administration	1 323	3.99	2.04	4	1	7	-0.03	-1.25	0.06
Q_11	Change topics (change to meet supervisor needs)	1 323	4.67	1.9	5	1	7	-0.49	-0.84	0.05
Q_12	Colloquiums and conferences	1 323	5.78	1.45	6	1	7	-1.22	0.94	0.04
Q_13	Consistent contact	1 323	5.35	1.67	6	1	7	-0.87	-0.14	0.05
Q_14	Examination process	1 323	5.49	1.66	6	1	7	-1.07	0.35	0.05
Q_15	Informal structure	1 323	5.49	1.59	6	1	7	-1.02	0.3	0.04
Q_16	Intervention	1 323	3.46	2	3	1	7	0.33	-1.14	0.05
Q_17	Progress reports	1 323	5.66	1.54	6	1	7	-1.16	0.71	0.04
Q_18	Recording meetings	1 323	5.72	1.49	6	1	7	-1.19	0.94	0.04
Q_19	Setting stages and goals	1 323	5.3	1.54	6	1	7	-0.82	0.09	0.04
Q_20	Setting the topic	1 323	5.33	1.6	6	1	7	-0.83	-0.01	0.04
Q_21	Supervisor availability	1 323	5.12	1.72	5	1	7	-0.68	-0.45	0.05
Q_22	Supervisor input	1 323	4.32	1.75	4	1	7	-0.17	-0.9	0.05
Q_23	Time flexibility	1 323	4.18	1.93	4	1	7	-0.12	-1.1	0.05
Q_24	Literature review	1 323	5.77	1.39	6	1	7	-1.22	1.18	0.04
Q_25	Methodologies	1 323	4.89	1.8	5	1	7	-0.56	-0.66	0.05
Q_26	Knowledge / expertise	1 323	4.08	1.99	4	1	7	-0.1	-1.15	0.05
Q_27	Referencing	1 323	5.82	1.52	6	1	7	-1.39	1.27	0.04
Q_28	Short training seminars	1 323	5.74	1.51	6	1	7	-1.21	0.84	0.04

#	Item	n	X̄	sd	Mdn	min	max	skew	kurt	se
Q_29	Statistics training (analysis)	1 323	4.96	1.89	5	1	7	-0.64	-0.69	0.05
Q_30	Time management	1 323	5.39	1.65	6	1	7	-0.92	-0.01	0.05
Q_31	Writing (/structure)	1 323	4.18	2.13	4	1	7	-0.14	-1.36	0.06
Q_32	Funding	1 323	6.05	1.34	7	1	7	-1.73	2.95	0.04
Q_33	Research funds	1 323	3.59	2.12	4	1	7	0.25	-1.23	0.06
Q_34	Equipment	1 323	4.91	1.97	5	1	7	-0.59	-0.85	0.05
Q_35	Ethics: policy material	1 323	3.7	2.13	4	1	7	0.17	-1.35	0.06
Q_36	Office space	1 323	4.05	2.16	4	1	7	0	-1.35	0.06
Q_37	Relevant articles	1 323	5.75	1.54	6	1	7	-1.32	1.14	0.04
Q_38	Communication	1 323	6.26	1.06	7	1	7	-1.77	3.89	0.03
Q_39	Exposure to academic discipline	1 323	5.35	1.7	6	1	7	-0.88	-0.07	0.05
Q_40	Informal meetings	1 323	4.84	1.88	5	1	7	-0.51	-0.85	0.05
Q_41	**Informal meetings [Approachable supervisors]**	**1 323**	**6.69**	**0.8**	**7**	**1**	**7**	**-4.06**	**21.22**	**0.02**
Q_42	Interactivity	1 323	4.57	1.79	5	1	7	-0.35	-0.84	0.05
Q_43	Interest	1 323	5.34	1.99	6	1	7	-1.07	-0.13	0.05
Q_44	Mentoring	1 323	5.7	1.59	6	1	7	-1.28	0.97	0.04
Q_45	Persistence / motivation	1 323	3.58	2.2	3	1	7	0.26	-1.39	0.06
Q_46	Positive feedback	1 323	5.19	1.81	6	1	7	-0.82	-0.31	0.05
Q_47	Proactive supervision	1 323	5.57	1.45	6	1	7	-1.06	0.77	0.04
Q_48	Problems assistance	1 323	3.01	1.71	3	1	7	0.5	-0.63	0.05
Q_49	Sensitivity to candidate needs	1 323	5.31	1.69	6	1	7	-0.84	-0.15	0.05
Q_50	Social	1 323	5.04	1.83	5	1	7	-0.71	-0.51	0.05
Q_51	Two-way commitment	1 323	2.67	1.84	2	1	7	0.95	-0.2	0.05

Supervision data was similarly processed as described in the previous chapter, and ultimately n = 180 completed unique responses were available during the data exploration phase of the analysis (Table 17). Mean scores for the supervision data ranged between M = 2.07 and M = 6.43, where 47 of the 51 variables ranged between M = 2.5 and M = 6. The standard deviation for the staff data ranged between SD = 0.94 and SD = 2.04. Supervisor respondents used the full range of responses on almost all items (1 to 7), except for Q_21, where the lowest score was 2. Similarly, on the staff responses, Q_41 contributed the most to skewness (-2.48) and kurtosis (8.28). Without item Q_41, skewness for the supervisor data ranged between -1.84 and 1.53, although 41 variables were within the -1 to 1 range. Kurtosis for the staff respondents on the remaining 50 items ranged between -1.33 and 4.18.

Table 17: Supervisor Likert questions descriptive statistics

#	Item	n	X̄	sd	Mdn	min	max	skew	kurt	se
Q_01	Contractual arrangements	180	5.15	1.82	6	1	7	-0.68	-0.72	0.14
Q_02	Deadlines	180	4.18	1.73	4	1	7	-0.14	-0.98	0.13
Q_03	Established timeframes	180	5.14	1.45	5	1	7	-0.79	0.24	0.11
Q_04	Independence	180	5.45	1.55	6	1	7	-0.98	0.13	0.12
Q_05	Staged write-up	180	4.35	1.72	5	1	7	-0.2	-1.02	0.13
Q_06	Standard of work (benchmark)	180	6.04	1.22	6	1	7	-1.54	2.3	0.09
Q_07	Supervisor turnaround time	180	3.94	1.95	4	1	7	-0.04	-1.33	0.15
Q_08	Timely feedback	180	5.97	1.17	6	1	7	-1.43	2.21	0.09
Q_09	Work independently	180	4.53	1.64	5	1	7	-0.29	-0.86	0.12
Q_10	Administration	180	4.11	1.85	4	1	7	-0.14	-1.12	0.14
Q_11	Change topics (change to meet supervisor needs)	180	3.63	2.04	3	1	7	0.26	-1.33	0.15
Q_12	Colloquiums and conferences	180	4.99	1.67	5	1	7	-0.72	-0.35	0.12
Q_13	Consistent contact	180	4.22	1.79	4	1	7	-0.12	-1.07	0.13
Q_14	Examination process	180	5.41	1.39	6	1	7	-0.95	0.8	0.1
Q_15	Informal structure	180	4.75	1.77	5	1	7	-0.55	-0.61	0.13
Q_16	Intervention	180	3.72	1.83	3	1	7	0.14	-1.17	0.14
Q_17	Progress reports	180	5.72	1.25	6	1	7	-1.12	1.4	0.09
Q_18	Recording meetings	180	4.78	1.83	5	1	7	-0.53	-0.75	0.14
Q_19	Setting stages and goals	180	5.47	1.37	6	1	7	-1.01	0.81	0.1
Q_20	Setting the topic	180	5.39	1.38	6	1	7	-0.97	0.66	0.1
Q_21	**Supervisor availability**	**180**	**6.3**	**0.97**	**7**	**2**	**7**	**-1.84**	**4.18**	**0.07**
Q_22	Supervisor input	180	3.99	1.52	4	1	7	0.06	-0.67	0.11
Q_23	Time flexibility	180	3.78	1.76	4	1	7	0.04	-1	0.13
Q_24	Literature review	180	5.31	1.4	6	1	7	-0.71	-0.06	0.1
Q_25	Methodologies	180	4.58	1.63	5	1	7	-0.4	-0.57	0.12
Q_26	Knowledge / expertise	180	4.27	1.6	4	1	7	-0.16	-0.78	0.12
Q_27	Referencing	180	6.02	1.2	6	1	7	-1.7	3.27	0.09
Q_28	Short training seminars	180	5.24	1.5	5.5	1	7	-0.91	0.38	0.11

#	Item	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Q_29	Statistics training (analysis)	180	3.24	1.75	3	1	7	0.51	-0.76	0.13
Q_30	Time management	180	5.35	1.36	6	1	7	-0.93	0.91	0.1
Q_31	Writing (/structure)	180	4.36	1.9	5	1	7	-0.27	-0.98	0.14
Q_32	Funding	180	5.31	1.59	6	1	7	-0.79	-0.18	0.12
Q_33	Research funds	180	2.07	1.76	1	1	7	1.53	1	0.13
Q_34	Equipment	180	4.04	1.86	4	1	7	-0.08	-1.03	0.14
Q_35	Ethics: policy material	180	3.83	1.93	4	1	7	0.15	-1.18	0.14
Q_36	Office space	180	2.79	1.91	2	1	7	0.82	-0.58	0.14
Q_37	Relevant articles	180	5.61	1.35	6	1	7	-1.13	1.33	0.1
Q_38	Communication	180	5.42	1.42	6	1	7	-1.09	0.84	0.11
Q_39	Exposure to academic discipline	180	4.86	1.92	5	1	7	-0.63	-0.77	0.14
Q_40	Informal meetings	180	4.33	1.74	5	1	7	-0.2	-0.99	0.13
Q_41	**Informal meetings [Approachable supervisors]**	**180**	**6.43**	**0.94**	**7**	**1**	**7**	**-2.48**	**8.28**	**0.07**
Q_42	Interactivity	180	3.9	1.69	4	1	7	0.12	-0.91	0.13
Q_43	Interest	180	3.86	1.93	4	1	7	-0.03	-1.24	0.14
Q_44	Mentoring	180	4.76	1.67	5	1	7	-0.53	-0.55	0.12
Q_45	Persistence / motivation	180	3.35	1.79	3	1	7	0.47	-0.81	0.13
Q_46	Positive feedback	180	5.41	1.42	6	1	7	-0.76	-0.13	0.11
Q_47	Proactive supervision	180	5.42	1.24	5	1	7	-0.75	0.63	0.09
Q_48	Problems assistance	180	2.94	1.48	3	1	7	0.49	-0.69	0.11
Q_49	Sensitivity to candidate needs	180	4.29	1.73	4	1	7	-0.32	-0.82	0.13
Q_50	Social	180	3.72	2	4	1	7	0.18	-1.22	0.15
Q_51	Two-way commitment	180	2.52	1.57	2	1	7	0.85	-0.33	0.12

Similar to the student data, Q_41 was the only variable to deviate too strongly from the cut-off criteria. The item content was concerned with the approachability of supervisors (Table 71), and it would thus be understandable that results would be skewed towards stronger agreement. Supervisors indicated that they perceived themselves to be more approachable (positive self-assessment), whereas students indicated they would need a supervisor to be approachable. Although supervisor approachability remains a vital point to assess, the wording of the instruments, specifically for students, may have led to biased responses, where asking students if they experienced their supervisors as approachable (student assessment of their experiences) would likely have yielded valuable information, although not consistent with the purposes of the current project.

To test for normality, a Shapiro-Wilks test was conducted on each item so as to measure univariant normality, and Mardia's test for multivariate normality was applied to the full-item datasets. As expected, staff and students' responses on all items deviated significantly from normality, likely due to the sample sizes. Shapiro-Wilks test statistics for students ranged between $W = 0.432$ and $W = 0.94$. The lowest statistic was measured on Q_41 ($W = 0.432$), whereas the next lowest score was $W = 0.718$ (Q_38) (Table 73). Multivariate skewness was 51 826.914, $p < .001$, whereas multivariate kurtosis was 115.05, $p < .001$, calculated from the correlation matrix of the dataset, both indicated significant deviation from normality. The QQ-plot for the students (Figure 49) indicated some deviation from normality, reiterating the caution presented in the method chapter (see section 4.8.1).

Shapiro-Wilks test statistics for supervisors ranged between $W = 0.631$ and $W = 0.952$. The lowest two variables were Q_41 ($W = 0.631$), and Q_33 ($W = 0.655$). The Q_33 asks supervisors if their students are funded with money they are responsible for, which may understandably also be slightly biased within the highly competitive higher education funding environment. The lowest statistic following these two scores was $W = 0.715$ (Q_21) (Table 74). Multivariate skewness for the supervisor dataset was 26 804.34, $p < .001$, whereas multivariate kurtosis was 6.44, $p < .001$, both indicating significant deviation from normality. The supervision data did not display a strong deviation from normality, particularly when visually inspecting the QQ-plot (Figure 50); however, some non-normality was found within the dataset.

Despite some indications of non-normality, the data may be useful within factor analysis approaches, given that the techniques are somewhat robust against violations of normality. Violation of this assumption did not signify that the project could not continue. Rather, due to of such violations, the generalisability of the data may be compromised (Field et al., 2012). It nonetheless creates a firm basis for additional study with the refined instruments. The following section provides a comprehensive overview of the CFA results.

5.2. Confirmatory factor analysis models

The following section provides an overview of the CFA models employed from students' perspectives. The section will discuss the interpretation of a summary of the goodness of fit statistics to compare the models presented. Models that did not present desirable fit statistics were modified by first removing variables with low loading. Due to the exploratory nature of this study, less strict cut-off statistics were utilised (Table 15), where items were considered for removal if loadings were below 0.4. After all items with low loadings were removed, the modification index was inspected so as to account for possible cross-loadings. Items with MI > 49 were modified. If items were cross-loaded with another latent factor, such items were considered for removal. Items in which MI scores indicated covariance of error terms within the same factors were allowed to covary[41] to improve fit statistics. To ensure a realistic comparison, the two baseline models (two-factor and six-factor) are presented unaltered for the CFA analysis; however, the adapted models are presented after alterations were applied. Tables are presented in the text below to provide an overall summary intended to make comparisons; however, full individual models are presented within Appendix E as raw outputs, available for review.

[41] Covariances are represented by two tildes: '~~'

5.2.1. Summary of CFA models

Two models could be identified within this study that may have presented operationalisations of the variables, as proposed by Gatfield (2005). The theoretical perspective posits that two overarching constructs or factors define supervision relationships: Structure (ST) and Support (SU). However, six sub-themes were proposed within each topic to operationalise each construct. Three sub-themes were assumed to refer to Structural aspects of supervision: Accountability and Stages (ST_AS); Organisation (ST_OR); and Skills provision (ST_SP). The remaining three sub-themes that formed part of Supportive aspects included: Financial (SU_FI); Material (SU_MA); Pastoral Care (SU_PC). The six-factor and two-factor models were inspected to ensure that the best explanation was considered for the results. To investigate the two-factor and six-factor models, a baseline CFA model for each was created, as specified in the instrument's design (Table 71). Each baseline was adapted to improve the models by removing items that did not contribute to the overall model.

The goodness of fit statistics of the baseline models of the six-factor model (CFA Six-Factor Model) as well as the two-factor model (CFA Two-Factor Model) did not meet the cut-off criteria as presented in Chapter Four (Table 15). The statistics for CFA Six-Factor Model were found to be: χ^2 = 6 319.449; df = 1 209; p < .001; χ^2/df = 5.227; RMSEA = 0.057; RMSEA CI_{90} = 0.058; SRMR = 0.065; CFI = 0.702; NFI = 0.657; AGFI = 0.774; AIC = 250 099.7 (Table 18). In comparison, results were slightly less acceptable for the baseline of the CFA Two-Factor Model: χ^2 = 7 135.825; df = 1 223; p < .001; χ^2/df = 5.835; RMSEA = 0.06; RMSEA CI_{90} = 0.062; SRMR = 0.066; CFI = 0.656; NFI = 0.613; AGFI = 0.749; AIC = 250 888.7 (Table 18). In both instances, RMSEA were the only indices within the acceptable range.

The modifications of both models substantially improved the fit indices (Appendix E: Instrument Validation). Overall, between 25 and 26 questions were removed from either model to facilitate this improvement. Modification on CFA Six-Factor Model are referred to as the CFA Six-Factor Modified Model showed marked improvement across all indices: χ^2 = 956.302; df = 258; p < .001; χ^2/df = 3.707; RMSEA = 0.045; RMSEA CI_{90} = 0.048; SRMR = 0.039; CFI = 0.93; NFI = 0.907; AGFI = 0.928; AIC = 117 067.7 (Table 18).

Modifications on CFA Two-Factor Model (CFA Two-Factor Modified Model) presented similar improvement across all indices: χ^2 = 959.53; df = 248; p < .001; χ^2/df = 3.869; RMSEA = 0.047; RMSEA CI_{90} = 0.05; SRMR = 0.038; CFI = 0.921; NFI = 0.897; AGFI = 0.929; AIC = 112 068.1 (Table 18), although CFI and NFI scores were slightly lower compared with CFA Six-Factor Modified Model, and the NFI did not quite reach the desired threshold. Both modified structures displayed markedly lower AIC scores compared to the baseline models, suggesting that either be used as an improved model. Within this instance, the two-factor model displayed a slightly lower AIC score. In contrast, the six-factor model presented a warning: "WARNING: covariance matrix of latent variables is not positive definite", because several of the proposed factors were highly correlated, resulting in a problem with multicollinearity.

Table 18: CFA Goodness-of-fit statistic summary (n = 1 323)

Model Code	CFA Six-Factor Model	CFA Six-Factor Modified Model **	CFA Two-Factor Model	CFA Two-Factor Modified Model	Cut-off
Factors	6	6	2	2	N/A
Variables	51	25	51	24	N/A
χ^2	6 319.449	956.302	7 135.825	959.53	See p-value
Df	1 209	258	1 223	248	N/A
Sig	0	0	0	0	P > 0.05 ***
χ^2/df	5.227	**3.707**	5.835	**3.869**	Mediocre (2-5)
RMSEA	**0.057**	**0.045**	**0.06**	**0.047**	Good (0.05 - 0.08)
RMSEA CI_{90}	**0.058**	**0.048**	**0.062**	**0.05**	Good (0.05 - 0.08)
SRMR	0.065	**0.039**	0.066	**0.038**	Good (< 0.05)
CFI	0.702	**0.93**	0.656	**0.921**	Good (0.9 - 0.95)
NFI	0.657	**0.907**	0.613	0.897	Good (0.9 - 0.95)
AGFI	0.774	**0.928**	0.749	**0.929**	Standard (AFGI > 0.90)
AIC	250 099.7	117 067.7	250 888.7	**112 068.1**	Lower value indicates better fit

* Raw outputs are available in Appendix E: Instrument Validation.

** Warning message "WARNING: covariance matrix of latent variables is not positive definite"

*** Significance on all models can be expected due to the sample size.

5.2.2. CFA factor loadings

The factor loadings for the six-factor models in Table 19 provide the estimates and the standardised factor loadings (Std.all) of each question included in the models. During the model modification, the standardised loadings were considered in deciding which variable ought to be removed from the model. Extant literature suggests that standardised loadings should be above 0.5 (Awang, 2012; Hair et al., 2014). However, due to the exploratory nature of this study, loadings below 0.4 were considered for removal. Questions were removed individually, and the fit statistics and standardised loadings were reconsidered after each removal. The table for the six-factor model indicated that the standardised factor loadings initially ranged between -0.181 and 0.763. At the same time, the modified model's standardised loadings ranged between 0.49 and 0.78 (Table 19). Both iterations of the model displayed moderate to high covariances between latent variables, ranging between 0.394 and 0.963, where only two covariances between latent variables were below 0.5 (Appendix E: Instrument Validation). The most notable aspect of the initial baseline models and subsequent explorations was that none of the negatively phrased questions loaded as intended on the factors where they were presumed to be positioned. This aspect of the analysis is explored in more depth later in this chapter and further discussions (see section 5.2.4). See figures 51 and 53 for a graphical representation of each model.

The factor loadings for the two-factor models in Table 20 provide the estimates and the standardised factor loadings of each question included in the model. Questions with standardised loadings below 0.4 were similarly considered for removal. The baseline two-factor model's standardised loadings ranged between -0.186 and 0.677, whereas the standardised loadings for the modified model ranged between 0.402 and 0.698 (Table 20). Covariances between the Structure and Support latent factor were 0.87 within the baseline model and 0.854 in the adapted two-factor model (Appendix E: Instrument Validation). These high covariances suggest a strong relationship between the latent factors from the students' perspective, which is just above the threshold of discriminant validity presented by Awang (2012). See figures 52 and 54 for a graphical representation of each model.

Within the analysis, the six-factor and two-factor baseline models both displayed numerous possible modifications where MI was above 49 (i.e., 50). The modification index was particularly useful in identifying cross-loading items that may warrant removal. Across every model, similar variables' error terms were allowed to covary, provided that it was congruent with the theoretical framework. Four pairs of questions were consistently considered through the chapter: Q_12 ~~ Q_28[42]; Q_34 ~~ Q_36; Q_24 ~~ Q_27; Q_25 ~~ Q_31.

- The first question pair refers to supervisors assisting students to become involved with conferences (Q_12), or that supervisors need to refer students to relevant workshops (Q_28), both considering activities that may assist students with additional learning opportunities at their level of study.
- The second question pair refers to students' access to equipment (Q_34) or access to suitable study space (Q_36), both of which may be considered additional resources.
- The third question pair refers to assistance with the literature review (Q_24) and avoiding plagiarism (Q_27), both referring to aspects of the writing process.
- Whereas the final question pair refers to supervisors directing the method that needs to be used in students' studies (Q_25), or supervisors needing to assist with the writing process (Q_31), both questions consider supervisors taking a more active approach in directing or guiding their student's work.

(Table 71)

Although the error terms of the abovementioned variables were covaried throughout the project, this procedure limits the generalisability of the models outside the present study population. Within the adapted six-factor CFA model, the following variables were allowed to covary: Q_24 ~~ Q_27; Q_25 ~~ Q_31. The adapted two-factor CFA model similarly allowed the following variables to covary: Q_34 ~~ Q_36; Q_24 ~~ Q_27; Q_25 ~~ Q_31 (Appendix E: Instrument Validation).

[42] Q_12 was later removed in each model due to high MI across multiple factors.

Table 19: Six-factor CFA model factor loadings

		CFA Six-Factor Model						CFA Six-Factor Modified Model					
Latent variables:	Item	Est.	SE	z-value	P>|z|	Std.lv	Std.all	Est.	SE	z-value	P>|z|	Std.lv	Std.all
ST_AS =~	Q_01	1.098	0.048	22.833	0	1.098	0.623	1.096	0.048	22.753	0	1.096	0.622
	Q_02	1.017	0.048	21.275	0	1.017	0.588	1.032	0.048	21.624	0	1.032	0.597
	Q_03	1.045	0.041	25.415	0	1.045	0.679	1.044	0.041	25.361	0	1.044	0.679
	Q_04	-0.186	0.06	-3.079	0.002	-0.186	-0.094	-	-	-	-	-	-
	Q_05	1.086	0.047	22.98	0	1.086	0.626	1.095	0.047	23.189	0	1.095	0.632
	Q_06	0.593	0.031	18.989	0	0.593	0.534	0.586	0.031	18.724	0	0.586	0.528
	Q_07	-0.104	0.063	-1.65	0.099	-0.104	-0.05	-	-	-	-	-	-
	Q_08	0.657	0.037	17.981	0	0.657	0.51	0.649	0.037	17.7	0	0.649	0.503
	Q_09	-0.017	0.057	-0.303	0.762	-0.017	-0.009	-	-	-	-	-	-
ST_OR =~	Q_10	0.64	0.057	11.168	0	0.64	0.314	-	-	-	-	-	-
	Q_11	0.75	0.053	14.235	0	0.75	0.394	-	-	-	-	-	-
	Q_12	0.897	0.037	23.945	0	0.897	0.619	-	-	-	-	-	-
	Q_13	1.007	0.044	23.132	0	1.007	0.602	1.048	0.044	23.818	0	1.048	0.627
	Q_14	0.847	0.044	19.057	0	0.847	0.512	0.864	0.045	19.141	0	0.864	0.522
	Q_15	0.937	0.042	22.5	0	0.937	0.589	0.987	0.042	23.513	0	0.987	0.62
	Q_16	-0.166	0.058	-2.871	0.004	-0.166	-0.083	-	-	-	-	-	-
	Q_17	1.053	0.039	27.17	0	1.053	0.684	1.068	0.039	27.059	0	1.068	0.693
	Q_18	0.573	0.041	13.847	0	0.573	0.384	-	-	-	-	-	-
	Q_19	0.867	0.041	21.361	0	0.867	0.564	0.887	0.041	21.531	0	0.887	0.577
	Q_20	0.099	0.046	2.136	0.033	0.099	0.062	-	-	-	-	-	-
	Q_21	0.67	0.048	14.067	0	0.67	0.39	-	-	-	-	-	-
	Q_22	0.327	0.05	6.533	0	0.327	0.187	-	-	-	-	-	-
	Q_23	0.347	0.055	6.274	0	0.347	0.18	-	-	-	-	-	-
ST_SP =~	Q_24	0.893	0.036	24.692	0	0.893	0.643	0.852	0.037	23.052	0	0.852	0.614
	Q_25	0.925	0.049	18.851	0	0.925	0.514	0.881	0.05	17.753	0	0.881	0.49
	Q_26	0.804	0.056	14.398	0	0.804	0.404	-	-	-	-	-	-

		CFA Six-Factor Model						CFA Six-Factor Modified Model					
	Q_27	0.926	0.04	23.04	0	0.926	0.608	0.875	0.041	21.298	0	0.875	0.575
	Q_28	0.926	0.04	23.332	0	0.926	0.614	0.901	0.04	22.444	0	0.901	0.598
	Q_29	0.213	0.055	3.858	0	0.213	0.113	-	-	-	-	-	-
	Q_30	0.926	0.044	20.876	0	0.926	0.561	0.95	0.044	21.427	0	0.95	0.575
	Q_31	1.137	0.058	19.689	0	1.137	0.533	1.1	0.058	18.855	0	1.1	0.516
SU_FI =~	Q_32	0.789	0.042	18.993	0	0.789	0.587	0.774	0.042	18.638	0	0.774	0.576
	Q_33	1.202	0.065	18.445	0	1.202	0.566	1.226	0.066	18.679	0	1.226	0.577
SU_MA =~	Q_34	1.499	0.051	29.236	0	1.499	0.763	1.533	0.052	29.41	0	1.533	0.78
	Q_35	0.198	0.065	3.059	0.002	0.198	0.093	-	-	-	-	-	-
	Q_36	1.601	0.057	28.246	0	1.601	0.741	1.668	0.057	29.08	0	1.668	0.772
	Q_37	0.737	0.044	16.734	0	0.737	0.478	-	-	-	-	-	-
SU_PC =~	Q_38	0.428	0.03	14.34	0	0.428	0.406	-	-	-	-	-	-
	Q_39	0.73	0.048	15.253	0	0.73	0.429	-	-	-	-	-	-
	Q_40	0.588	0.054	10.861	0	0.588	0.313	-	-	-	-	-	-
	Q_41	0.352	0.022	15.679	0	0.352	0.44	-	-	-	-	-	-
	Q_42	0.481	0.052	9.258	0	0.481	0.269	-	-	-	-	-	-
	Q_43	0.268	0.059	4.58	0	0.268	0.135	-	-	-	-	-	-
	Q_44	0.971	0.042	23.003	0	0.971	0.611	0.984	0.043	22.624	0	0.984	0.619
	Q_45	-0.382	0.065	-5.921	0	-0.382	-0.174	-	-	-	-	-	-
	Q_46	0.786	0.051	15.501	0	0.786	0.435	-	-	-	-	-	-
	Q_47	0.939	0.038	24.662	0	0.939	0.646	0.919	0.04	23.226	0	0.919	0.633
	Q_48	-0.31	0.05	-6.163	0	-0.31	-0.181	-	-	-	-	-	-
	Q_49	0.837	0.047	17.897	0	0.837	0.494	0.84	0.048	17.466	0	0.84	0.496
	Q_50	1.095	0.049	22.361	0	1.095	0.597	1.15	0.05	22.962	0	1.15	0.627
	Q_51	-0.065	0.054	-1.196	0.232	-0.065	-0.035	-	-	-	-	-	-

Table 20: Two-factor CFA model factor loadings

		CFA Two-Factor Model						CFA Two-Factor Modified Model					
Latent variables:	Item	Est.	SE	z-value	P>|z|	Std.lv	Std.all	Est.	SE	z-value	P>|z|	Std.lv	Std.all
Structure =~	Q_01	0.905	0.047	19.243	0	0.905	0.513	-	-	-	-	-	-
	Q_02	0.709	0.047	14.936	0	0.709	0.41	-	-	-	-	-	-
	Q_03	0.861	0.04	21.31	0	0.861	0.56	0.829	0.041	20.02	0	0.829	0.539
	Q_04	-0.262	0.057	-4.604	0	-0.262	-0.132	-	-	-	-	-	-
	Q_05	0.838	0.047	17.94	0	0.838	0.483	-	-	-	-	-	-
	Q_06	0.518	0.03	17.27	0	0.518	0.467	0.503	0.031	16.419	0	0.503	0.453
	Q_07	0.088	0.059	1.479	0.139	0.088	0.043	-	-	-	-	-	-
	Q_08	0.551	0.035	15.614	0	0.551	0.427	0.519	0.036	14.387	0	0.519	0.402
	Q_09	-0.07	0.054	-1.298	0.194	-0.07	-0.037	-	-	-	-	-	-
	Q_10	0.633	0.057	11.106	0	0.633	0.311	-	-	-	-	-	-
	Q_11	0.749	0.052	14.292	0	0.749	0.394	-	-	-	-	-	-
	Q_12	0.883	0.037	23.648	0	0.883	0.61	-	-	-	-	-	-
	Q_13	1.002	0.043	23.134	0	1.002	0.599	0.985	0.044	22.305	0	0.985	0.589
	Q_14	0.838	0.044	18.928	0	0.838	0.506	0.856	0.045	19.094	0	0.856	0.517
	Q_15	0.933	0.041	22.551	0	0.933	0.587	0.949	0.042	22.645	0	0.949	0.597
	Q_16	-0.168	0.057	-2.924	0.003	-0.168	-0.084	-	-	-	-	-	-
	Q_17	1.043	0.039	27.036	0	1.043	0.677	1.075	0.039	27.676	0	1.075	0.698
	Q_18	0.571	0.041	13.86	0	0.571	0.383	-	-	-	-	-	-
	Q_19	0.871	0.04	21.633	0	0.871	0.567	0.888	0.041	21.771	0	0.888	0.578
	Q_20	0.1	0.046	2.183	0.029	0.1	0.063	-	-	-	-	-	-
	Q_21	0.656	0.047	13.817	0	0.656	0.382	-	-	-	-	-	-
	Q_22	0.318	0.05	6.375	0	0.318	0.182	-	-	-	-	-	-
	Q_23	0.337	0.055	6.121	0	0.337	0.175	-	-	-	-	-	-
	Q_24	0.855	0.036	23.951	0	0.855	0.616	0.856	0.036	23.54	0	0.856	0.617
	Q_25	0.882	0.048	18.243	0	0.882	0.49	0.859	0.049	17.375	0	0.859	0.477
	Q_26	0.747	0.055	13.576	0	0.747	0.376	-	-	-	-	-	-

		CFA Two-Factor Model						CFA Two-Factor Modified Model					
	Q_27	0.887	0.04	22.379	0	0.887	0.583	0.877	0.041	21.654	0	0.877	0.577
	Q_28	0.898	0.039	22.98	0	0.898	0.596	0.893	0.04	22.464	0	0.893	0.593
	Q_29	0.204	0.054	3.771	0	0.204	0.108	-	-	-	-	-	-
	Q_30	0.92	0.043	21.179	0	0.92	0.557	0.955	0.044	21.797	0	0.955	0.578
	Q_31	1.067	0.057	18.68	0	1.067	0.5	1.059	0.058	18.21	0	1.059	0.497
Support =~	Q_32	0.772	0.036	21.595	0	0.772	0.574	0.759	0.037	20.799	0	0.759	0.565
	Q_33	1.06	0.058	18.314	0	1.06	0.499	-	-	-	-	-	-
	Q_34	1.218	0.051	23.751	0	1.218	0.62	1.147	0.053	21.585	0	1.147	0.584
	Q_35	0.143	0.062	2.302	0.021	0.143	0.067	-	-	-	-	-	-
	Q_36	1.299	0.057	22.857	0	1.299	0.601	1.196	0.059	20.243	0	1.196	0.554
	Q_37	0.774	0.042	18.431	0	0.774	0.502	0.79	0.043	18.545	0	0.79	0.512
	Q_38	0.398	0.03	13.417	0	0.398	0.377	-	-	-	-	-	-
	Q_39	0.711	0.047	14.995	0	0.711	0.418	0.695	0.048	14.356	0	0.695	0.408
	Q_40	0.594	0.053	11.108	0	0.594	0.316	-	-	-	-	-	-
	Q_41	0.327	0.022	14.64	0	0.327	0.409	-	-	-	-	-	-
	Q_42	0.476	0.051	9.265	0	0.476	0.266	-	-	-	-	-	-
	Q_43	0.237	0.058	4.087	0	0.237	0.119	-	-	-	-	-	-
	Q_44	0.933	0.042	22.216	0	0.933	0.587	0.959	0.043	22.556	0	0.959	0.604
	Q_45	-0.372	0.064	-5.824	0	-0.372	-0.169	-	-	-	-	-	-
	Q_46	0.757	0.05	15.062	0	0.757	0.42	0.771	0.051	15.098	0	0.771	0.427
	Q_47	0.901	0.038	23.762	0	0.901	0.62	0.923	0.038	24.022	0	0.923	0.635
	Q_48	-0.319	0.05	-6.433	0	-0.319	-0.186	-	-	-	-	-	-
	Q_49	0.823	0.046	17.768	0	0.823	0.486	0.836	0.047	17.764	0	0.836	0.494
	Q_50	1.11	0.048	23.055	0	1.11	0.605	1.129	0.049	23.108	0	1.129	0.616
	Q_51	-0.049	0.054	-0.904	0.366	-0.049	-0.026	-	-	-	-	-	-

The reliability of the baseline six-factor model indicates that most of the factors would be considered reliable within this analysis. Factors typically displayed CR above 0.6, considered reliable within this study, whereas alpha scores were typically above 0.5. The factor concerned with the financial support of students typically scored just below 0.5; however, the factor also only consisted of two variables, typically considered insufficient for a complete analysis. Additionally, several factors displayed possible negative correlations, suggesting one or more variables needed to be reverse-scored (Table 21).

Comparably, the modified six-factor model displayed marked improvement in most reliability scores, with most factors' CR and alphas measuring above 0.65. As no changes were made to the factor measuring financial support, the same scores were measured. Similarly, the factor measuring material support only consisted of two variables within the modified structure. None of the factors displayed the need to reverse score variables. It should be noted that within both models, the AVE was measured below 0.5 for all factors, except for material support within the modified model (Table 21). This suggests that the model does not display the desired convergent and discriminant validity.

Table 21: Six-factor model reliability

	CFA Six-Factor Model			CFA Six-Factor Modified Model		
	Alpha	CR	AVE	Alpha	CR	AVE
ST_AS	*0.57	0.629	0.238	0.76	0.766	0.356
ST_OR	*0.71	0.722	0.198	0.74	0.746	0.373
ST_SP	0.71	0.733	0.275	0.75	0.735	0.317
SU_FI	**0.46	0.499	0.332	**0.46	0.499	0.332
SU_MA	0.55	0.621	0.342	**0.75	0.752	0.602
SU_PC	*0.6	0.623	0.17	0.68	0.686	0.356

* Variables were negatively correlated

** Analysis based on two variables

The two-factor baseline model also displayed high CR and alpha scores above 0.7; however, the alpha scores also suggested that some variables needed to be reverse scored. The modified two-factor model's CR and alpha scores were somewhat improved; both were above 0.8, signifying very good reliability. Although there was a marked improvement between AVE scores, both models were below 0.5, indicating possible difficulties with convergent and discriminant validity (Table 22).

Table 22: Two-factor model reliability

	CFA Two-Factor Model			CFA Two-Factor Modified Model		
	Alpha	CR	AVE	Alpha	CR	AVE
Structure	*0.84	0.851	0.199	0.86	0.86	0.309
Support	*0.74	0.757	0.191	0.81	0.806	0.297

* Variables were negatively correlated

Overall, the modified models conformed to the validity criteria by presenting acceptable fit statistics and factor loadings. In addition, most of the factors showed acceptable levels of reliability. The modified two-factor model seemed to have stronger support regarding validity testing and the reliability statistics. However, the models were determined from a theoretical basis. There were some indications that there may have been a need for better differentiation between the theorised factors (particularly with the two-factor model). In addition, several question items were removed from further analysis based on the CFA findings. Thus, considering the exploratory nature of the study, it was prudent to follow with an investigation of an EFA, so as to ensure that the correct factor structure was used within this project.

5.2.3. Exploratory factor analysis

Due to the exploratory nature of the current study, alternative models were investigated through the utilisation of EFA (Jackson et al., 2009). To conduct this analysis, the whole student data set (n = 1 323) was randomly split into a training data set (n = 595), utilised in the EFA analysis, and a test data set (n = 728), utilised in the CFA analysis of the EFA model (Hair et al., 2014; Orcan, 2018). Exploration of the data through the EFA approaches displayed the possibility of three model structures, consisting of either two-factor, three-factor, or four-factor models. Consistent with the theoretical approach, the analysis utilised an orthogonal rotation (Varimax). However, an oblique rotation (Direct Oblimin) was also considered, due to practicalities in the analysis. As a result, an additional six models were investigated in the analysis as possible alternatives.

Each EFA analysis started with the total number of variables, specifying the number of factors and rotation. Items were reduced iteratively, until a simple interpretable structure was found. Items were removed based on discussed criteria, factor loadings below 0.4, and low commonalities; however, theoretical judgements additionally impacted the analysis. Each EFA model was tested with a larger Test sample set through a CFA. Each model was adapted and improved, based on the CFA that was conducted and compared with other models. Covariances within the CFA models were only specified when they made theoretical sense. Similar specifications were made across models (as briefly explained in this chapter's first CFA analysis section 5.2.2).

The EFA reporting structure utilised within this chapter was adapted from the suggestions by made Field et al. (2012). Thus, each EFA discussion includes a brief description of the measured KMO scores, Bartlett's test for sphericity results, and the determinant score. The eigenvalues, parallel analysis, scree plot, and total variance explained are outlined as considerations for the proposed factor structure. Factor loadings and commonalities are briefly considered, alongside a brief description of the latent factors. The report of the CFA tests is constructed as presented within the first half of this chapter; however, each model is described individually. The section summarises an in-depth discussion of variable structures across models and total model fit comparisons between CFA structures. After this, the chapter concludes with a description and argument for the chosen model. CFA models were adapted where necessary, and thus may not have retained the full number of variables presented in the initial EFA analysis. Variables were removed due to challenges with item loadings or specified within the modification index.

5.2.3.1. EFA Two-Factor Orthogonal Model

The first model is represented by two factors, utilising an orthogonal rotation. The two-factor analysis was conducted with Varimax rotation, where 23 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (253) = 4 360.888, $p < .001$. The overall KMO measure was .92. The KMO of the individual retained variables was consistently

> 0.8, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0005825219. A parallel analysis indicated that four factors or two components needed to be retained. There were two factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible two-factor structure (Figure 14), suggesting that the number of factors would be adequate for this analysis. The sums of squared loadings (SS loadings)[43] were MR1 = 4.75 and MR2 = 3.24, whereas the EFA explained a total of 35% of the variance. Loadings within this iteration were above 0.42, and variable commonalities were above 0.2. Factors could be identified as: Structure; Support and reflected the theoretical framework; however, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

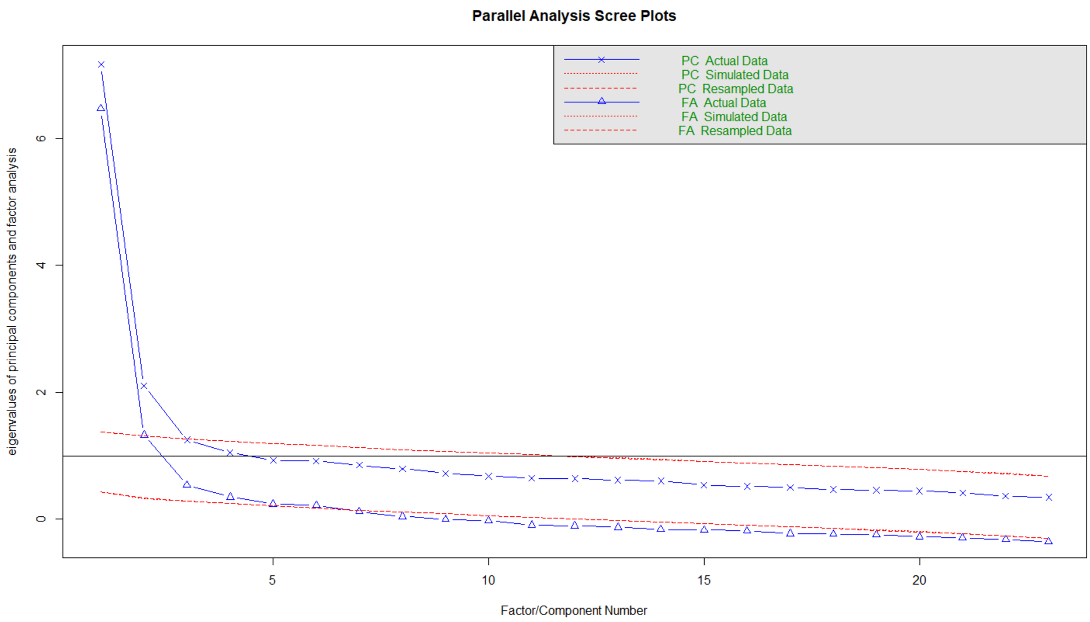


Figure 14: Scree plot EFA Two-Factor Orthogonal Model

[43] "The eigenvalues associated with each factor represent the variance explained by that particular linear component. R calls these SS loadings (sums of squared loadings)…" (Field et al., 2012, p. 780).

In conducting the CFA, 22 variables were retained. Within this analysis, the goodness of fit statistics of the EFA Two-Factor Orthogonal Model: $\chi^2 = 623.213$; df = 205; $p < .001$; $\chi^2/df = 3.04$; RMSEA = 0.053; RMSEA CI_{90} = 0.058; SRMR = 0.05; CFI = 0.91; NFI = 0.872; AGFI = 0.91; AIC = 56 381.66 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Two-Factor Orthogonal Model were above 0.475 (Appendix E: Instrument Validation). Within the analysis, six items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28; Q_34 ~~ Q_36; Q_24 ~~ Q_27. Latent variables were measured to covary, specifically: Structure ~~ Support = 0.668 (Figure 15). The modification index indicated no more covariances to consider with MI > 49. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.804, alpha > 0.8). However, AVE scores were typically < 0.342, suggesting similar issues with convergent and discriminant validity as previously reported (Table 23).

Table 23: CFA factor loadings and reliability EFA Two-Factor Orthogonal Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.80	0.80	0.34	Q_01	1.07	0.06	16.76	0.00	1.07	0.61	0.77
				Q_02	1.00	0.06	16.01	0.00	1.00	0.59	0.78
				Q_03	1.02	0.06	18.12	0.00	1.02	0.65	0.77
				Q_05	1.07	0.06	17.00	0.00	1.07	0.62	0.77
				Q_06	0.56	0.04	13.17	0.00	0.56	0.50	0.79
				Q_08	0.60	0.05	12.71	0.00	0.60	0.48	0.79
				Q_13	1.07	0.06	18.00	0.00	1.07	0.65	0.78
				Q_15	0.87	0.06	14.60	0.00	0.87	0.55	0.78
Support	0.87	0.86	0.31	Q_12	0.88	0.05	17.78	0.00	0.88	0.63	0.85
				Q_24	0.82	0.05	16.60	0.00	0.82	0.60	0.86
				Q_27	0.83	0.06	14.79	0.00	0.83	0.54	0.86
				Q_28	0.88	0.05	16.24	0.00	0.88	0.59	0.86
				Q_31	1.02	0.08	12.92	0.00	1.02	0.48	0.86
				Q_32	0.75	0.05	15.66	0.00	0.75	0.57	0.86
				Q_33	1.00	0.08	12.69	0.00	1.00	0.48	0.86
				Q_34	1.10	0.07	15.97	0.00	1.10	0.58	0.85
				Q_36	1.24	0.08	15.96	0.00	1.24	0.58	0.85

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
				Q_37	0.78	0.06	13.83	0.00	0.78	0.51	0.86
				Q_44	0.89	0.06	15.37	0.00	0.89	0.56	0.86
				Q_47	0.86	0.05	16.78	0.00	0.86	0.60	0.86
				Q_49	0.81	0.06	13.04	0.00	0.81	0.49	0.86
				Q_50	1.13	0.07	17.08	0.00	1.13	0.61	0.85

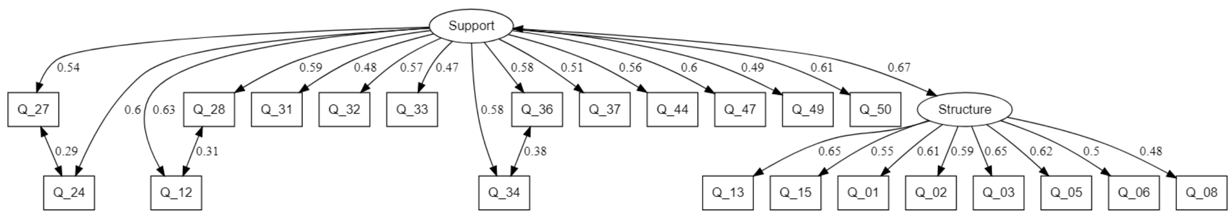


Figure 15: CFA factor loadings EFA Two-Factor Orthogonal Model

5.2.3.2. EFA Two-Factor Oblique Model

The second model is represented by two factors, utilising an oblique rotation. The two-factor analysis was conducted with Direct Oblimin rotation, where 24 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (276) = 4 582.313, $p < .001$. The overall KMO measure was 0.93. The KMO of the individual retained variables was consistently > 0.8, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0003973145. A parallel analysis indicated that six factors or two components needed to be retained. There were two factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible two-factor structure (Figure 16), suggesting that the number of factors would be adequate for this analysis. SS loadings were MR1 = 5.43 and MR2 = 2.83, whereas the EFA explained 34% of the variance. Loadings within this iteration were above 0.41, and variable commonalities were above 0.18. Factors could be identified as: Structure; Support and reflected the theoretical framework; however, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

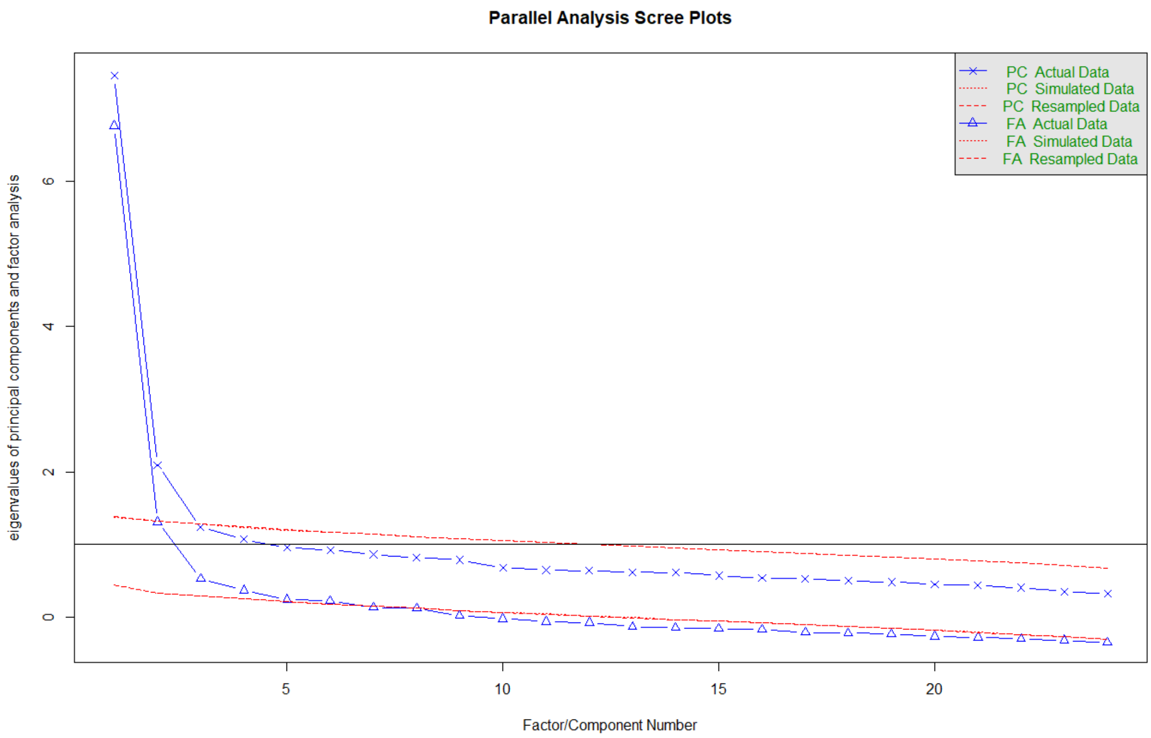


Figure 16: Scree plot EFA Two-Factor Oblique Model

In conducting the CFA, 21 variables were retained. Within this analysis, the goodness of fit statistics of the EFA Two-Factor Oblique Model: $\chi^2 = 494.315$; df = 185; $p < .001$; $\chi^2/df = 2.672$; RMSEA = 0.048; RMSEA $CI_{90} = 0.053$; SRMR = 0.044; CFI = 0.93; NFI = 0.893; AGFI = 0.923; AIC = 53 671.58 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Two-Factor Oblique Model were above 0.462 (Appendix E: Instrument Validation). Within the analysis, six items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28; Q_34 ~~ Q_36; Q_24 ~~ Q_27. Latent variables were measured to covary, specifically: Structure ~~ Support = 0.613 (Figure 17). The modification index indicated no more covariances to consider with MI > 49. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.77, alpha > 0.76). However, AVE scores were typically < 0.36, suggesting similar issues with convergent and discriminant validity, as previously reported (Table 24).

Table 24: CFA factor loadings and reliability EFA Two-Factor Oblique Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.76	0.77	0.36	Q_01	1.03	0.07	15.71	0	1.03	0.59	0.72
				Q_02	1.08	0.06	17.19	0	1.08	0.64	0.72
				Q_03	1.09	0.06	19.22	0	1.09	0.70	0.71
				Q_05	1.08	0.06	16.77	0	1.08	0.62	0.71
				Q_06	0.58	0.04	13.41	0	0.58	0.52	0.75
				Q_08	0.63	0.05	13.10	0	0.63	0.51	0.75
Support	0.88	0.88	0.32	Q_12	0.89	0.05	18.16	0	0.89	0.64	0.87
				Q_17	1.02	0.05	18.73	0	1.02	0.65	0.87
				Q_24	0.83	0.05	17.03	0	0.83	0.61	0.87
				Q_27	0.86	0.06	15.58	0	0.86	0.57	0.87
				Q_28	0.88	0.05	16.35	0	0.88	0.59	0.87
				Q_31	1.01	0.08	12.84	0	1.01	0.48	0.87
				Q_32	0.74	0.05	15.42	0	0.74	0.56	0.87
				Q_33	0.98	0.08	12.36	0	0.98	0.46	0.87
				Q_34	1.11	0.07	16.29	0	1.11	0.59	0.86
				Q_36	1.22	0.08	15.79	0	1.22	0.57	0.87
				Q_37	0.79	0.06	14.05	0	0.79	0.52	0.87
				Q_44	0.88	0.06	15.15	0	0.88	0.55	0.87
				Q_47	0.86	0.05	16.87	0	0.86	0.60	0.87
				Q_49	0.78	0.06	12.63	0	0.78	0.47	0.87
				Q_50	1.11	0.07	16.82	0	1.11	0.60	0.87

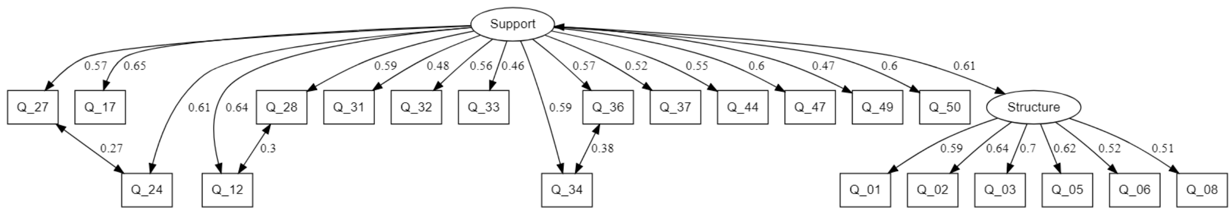


Figure 17: CFA factor loadings EFA Two-Factor Oblique Model

5.2.3.3. EFA Three-Factor Orthogonal Model

The third model is represented by three factors, utilising an orthogonal rotation. The three-factor analysis was conducted with Varimax rotation, where 27 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (351) = 4 791.264, $p < .001$. The overall KMO measure was 0.91. The KMO of the individual retained variables was consistently > 0.6, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0002741381. A parallel analysis indicated that six factors or three components needed to be retained. There were three factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible four-factor structure (Figure 18), suggesting that the number of factors would be adequate for this analysis. SS loadings were MR1 = 4.89, MR2 = 3.20, and MR3 = 1.28, whereas the EFA explained 35% of the variance. Loadings within this iteration were above 0.41, and variable commonalities were above 0.19. Factors were identified as: Structure; Support; and Independence, and reflected the theoretical framework. However, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

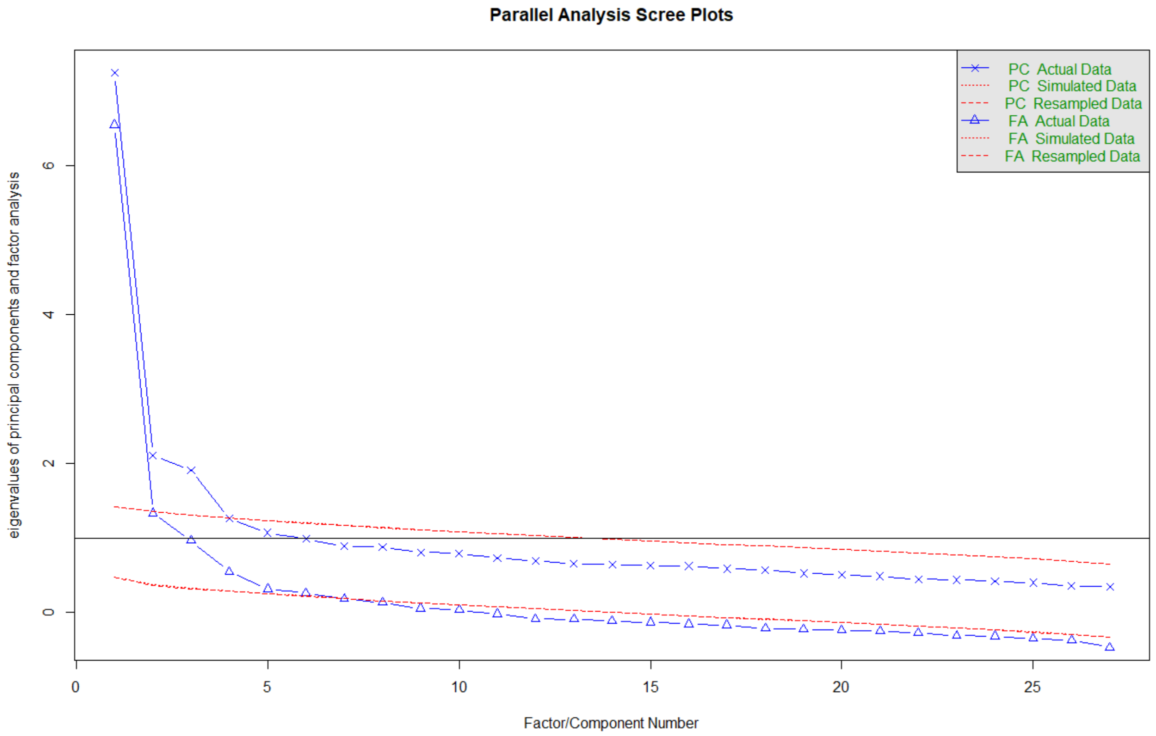


Figure 18: Scree plot EFA Three-Factor Orthogonal Model

In conducting the CFA, 26 variables were retained. Within this analysis, the goodness of fit statistics of the EFA Three-Factor Orthogonal Model: χ^2 = 792.092; df = 293; p < .001; χ^2/df = 2.703; RMSEA = 0.048; RMSEA CI_{90} = 0.052; SRMR = 0.055; CFI = 0.9; NFI = 0.851; AGFI = 0.907; AIC = 68 001.77 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Three-Factor Orthogonal Model were above 0.407 (Appendix E: Instrument Validation). Within the analysis, six items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28; Q_34 ~~ Q_36; Q_24 ~~ Q_27. Latent variables were measured to covary, specifically: Structure ~~ Support = 0.668; Structure ~~ Independence = 0.058; Support ~~ Independence = 0.096 (Figure 19). The modification index indicated no more covariances to consider with MI > 49. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.59, alpha > 0.58). However, AVE scores were typically < 34, suggesting similar issues with convergent and discriminant validity as previously reported (Table 25).

Table 25: CFA factor loadings and reliability EFA Three-Factor Orthogonal Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.80	0.80	0.34	Q_01	1.07	0.06	16.76	0	1.07	0.61	0.77
				Q_02	1.00	0.06	16.01	0	1.00	0.59	0.78
				Q_03	1.02	0.06	18.13	0	1.02	0.65	0.77
				Q_05	1.07	0.06	17.00	0	1.07	0.62	0.77
				Q_06	0.56	0.04	13.17	0	0.56	0.50	0.79
				Q_08	0.60	0.05	12.71	0	0.60	0.48	0.79
				Q_13	1.07	0.06	17.99	0	1.07	0.65	0.78
				Q_15	0.87	0.06	14.60	0	0.87	0.55	0.78
Support	0.87	0.86	0.31	Q_12	0.89	0.05	17.80	0	0.89	0.63	0.85
				Q_24	0.81	0.05	16.56	0	0.81	0.60	0.86
				Q_27	0.83	0.06	14.78	0	0.83	0.54	0.86
				Q_28	0.88	0.05	16.26	0	0.88	0.59	0.86
				Q_31	1.02	0.08	12.91	0	1.02	0.48	0.86
				Q_32	0.75	0.05	15.66	0	0.75	0.57	0.86
				Q_33	1.01	0.08	12.72	0	1.01	0.48	0.86
				Q_34	1.10	0.07	15.97	0	1.10	0.58	0.85
				Q_36	1.24	0.08	15.98	0	1.24	0.58	0.85
				Q_37	0.78	0.06	13.84	0	0.78	0.51	0.86
				Q_44	0.89	0.06	15.36	0	0.89	0.56	0.86
				Q_47	0.86	0.05	16.78	0	0.86	0.60	0.86
				Q_49	0.81	0.06	13.04	0	0.81	0.49	0.86
				Q_50	1.13	0.07	17.07	0	1.13	0.61	0.85
Independence	0.58	0.59	0.27	Q_04	0.88	0.09	9.62	0	0.88	0.45	0.56
				Q_09	1.19	0.09	12.74	0	1.19	0.64	0.42
				Q_22	0.99	0.09	11.73	0	0.99	0.57	0.49
				Q_29	0.76	0.09	8.74	0	0.76	0.41	0.56

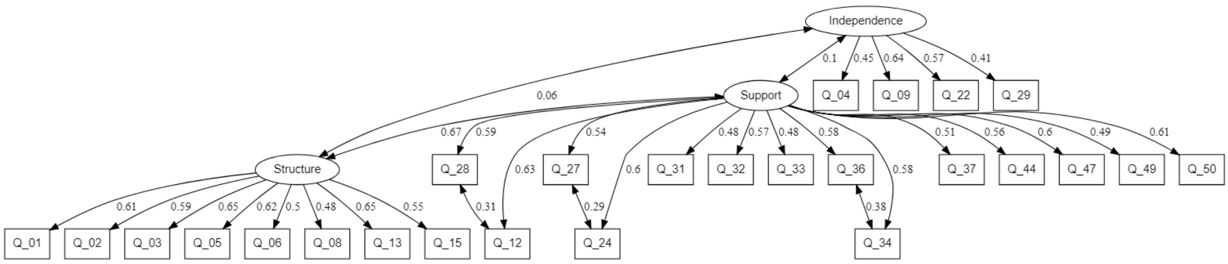


Figure 19: CFA factor loadings EFA Three-Factor Orthogonal Model

5.2.3.4. EFA Three-Factor Oblique Model

The fourth model is represented by three factors, utilising an oblique rotation. The three-factor analysis was conducted with Direct Oblimin rotation, where 26 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (325) = 4 479.93, $p < .001$. The overall KMO measure was 0.9. The KMO of the individual retained variables was consistently > 0.6, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0004691673. A parallel analysis indicated that four factors, or three components, needed to be retained. There were three factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible four-factor structure (Figure 20), suggesting that the number of factors would be adequate for this analysis. SS loadings were MR1 = 5.05, MR2 = 1.46, and MR3 = 2.51, whereas the EFA explained 35% of the variance. Loadings within this iteration were above 0.41, and variable commonalities were above 0.17. Factors could be identified as: Structure; Support; and Independence, and reflected the theoretical framework. However, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

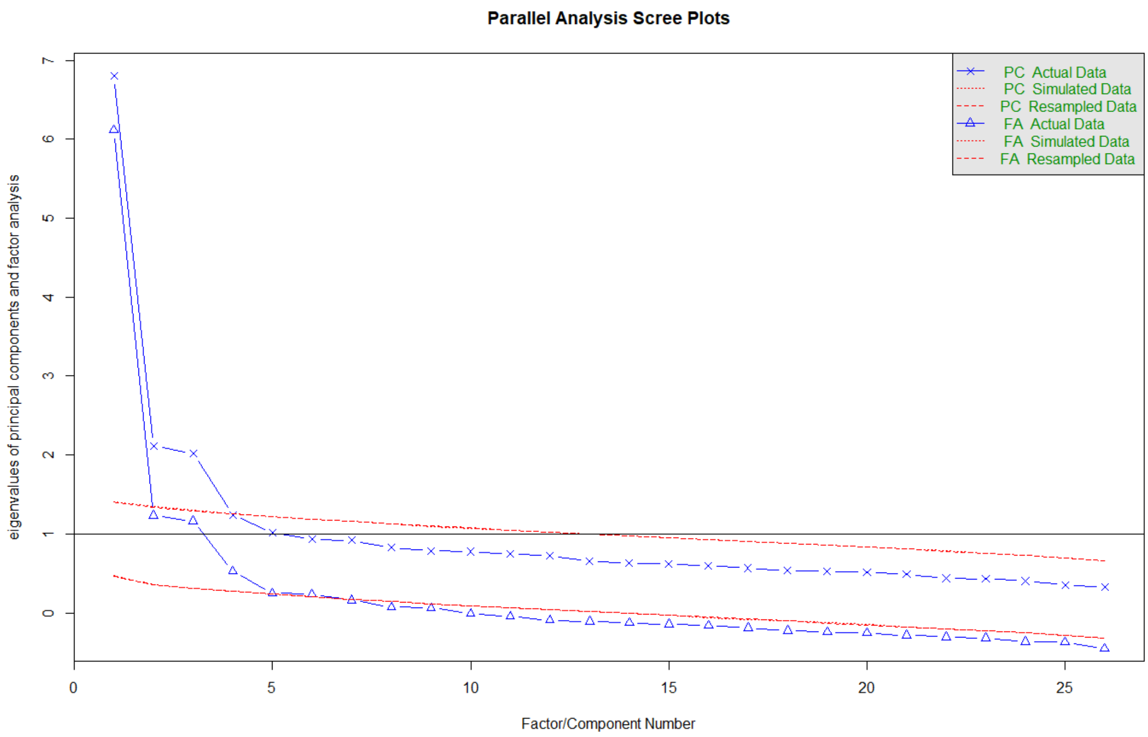


Figure 20: Scree plot EFA Three-Factor Oblique Model

In conducting the CFA, 24 variables were retained. Within this analysis, the goodness of fit statistics of the EFA Three-Factor Oblique Model: χ^2 = 627.576; df = 246; p < .001; χ^2/df = 2.551; RMSEA = 0.046; RMSEA CI_{90} = 0.051; SRMR = 0.056; CFI = 0.917; NFI = 0.871; AGFI = 0.918; AIC = 62 852.43 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Three-Factor Oblique Model were above 0.467 (Appendix E: Instrument Validation). Within the analysis, six items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28; Q_34 ~~ Q_36; Q_24 ~~ Q_27. Latent variables were measured to covary specifically: Structure ~~ Support = 0.618; Structure ~~ Independence = 0.01; Support ~~ Independence = -0.041 (Figure 21). The modification index indicated one more covariance to consider with MI > 49, between the latent variable Support and the Independence question Q_22 with an MI = 49.37. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.62, alpha > 0.6). However, AVE scores were typically < 0.36, suggesting similar issues with convergent and discriminant validity as previously reported (Table 26).

Table 26: CFA factor loadings and reliability EFA Three-Factor Oblique Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.76	0.77	0.36	Q_01	1.03	0.07	15.71	0	1.03	0.59	0.72
				Q_02	1.08	0.06	17.19	0	1.08	0.64	0.72
				Q_03	1.09	0.06	19.23	0	1.09	0.70	0.71
				Q_05	1.08	0.06	16.80	0	1.08	0.63	0.71
				Q_06	0.57	0.04	13.38	0	0.57	0.52	0.75
				Q_08	0.63	0.05	13.10	0	0.63	0.51	0.75
Support	0.87	0.87	0.32	Q_12	0.90	0.05	18.09	0	0.90	0.64	0.86
				Q_17	1.02	0.06	18.65	0	1.02	0.65	0.86
				Q_24	0.83	0.05	16.90	0	0.83	0.61	0.86
				Q_27	0.86	0.06	15.48	0	0.86	0.56	0.86
				Q_28	0.87	0.05	16.04	0	0.87	0.58	0.86
				Q_31	1.01	0.08	12.88	0	1.01	0.48	0.87
				Q_32	0.73	0.05	15.12	0	0.73	0.55	0.86
				Q_33	0.99	0.08	12.46	0	0.99	0.47	0.87
				Q_34	1.10	0.07	15.94	0	1.10	0.58	0.86
				Q_36	1.22	0.08	15.72	0	1.22	0.57	0.86
				Q_44	0.89	0.06	15.38	0	0.89	0.56	0.86
				Q_47	0.87	0.05	16.86	0	0.87	0.60	0.86
				Q_49	0.78	0.06	12.67	0	0.78	0.47	0.87
				Q_50	1.11	0.07	16.73	0	1.11	0.60	0.86
Independence	0.60	0.62	0.30	Q_04	0.98	0.09	10.89	0	0.98	0.50	0.55
				Q_09	1.26	0.09	14.05	0	1.26	0.68	0.45
				Q_16	0.99	0.09	10.98	0	0.99	0.50	0.56
				Q_22	0.85	0.08	10.72	0	0.85	0.49	0.54

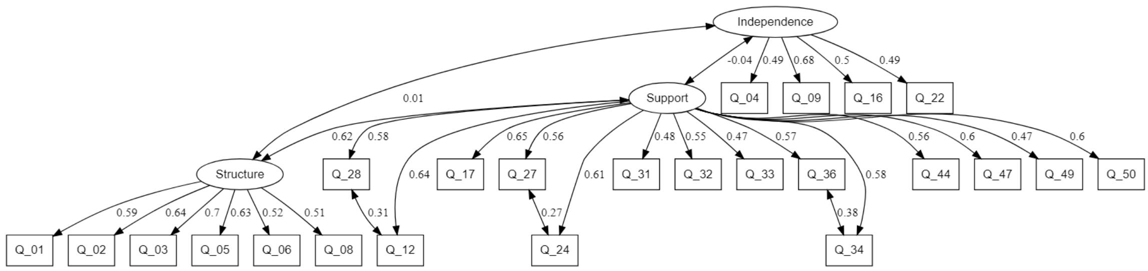


Figure 21: CFA factor loadings EFA Three-Factor Oblique Model

5.2.3.5. EFA Four-Factor Orthogonal Model

The fifth model is represented by four factors, utilising an orthogonal rotation. The four-factor analysis was conducted with Varimax rotation, where 28 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (378) = 4 981.18, $p < .001$. The overall KMO measure was .91. The KMO of the individual retained variables was consistently > 0.6, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0001970894. A parallel analysis indicated that six factors or three components needed to be retained. There were three factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible four-factor structure (Figure 22), suggesting that the number of factors would be adequate for this analysis. SS loadings were MR1 = 4.41, MR2 = 2.98, MR3 = 1.46, MR4 = 1.57, whereas the EFA explained a total of 37% of the variance. Loadings within this iteration were above 0.41, and variable commonalities were above 0.18. Factors could be identified as: Structure; Support; Independence; and Resources, and reflected the theoretical framework; however, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

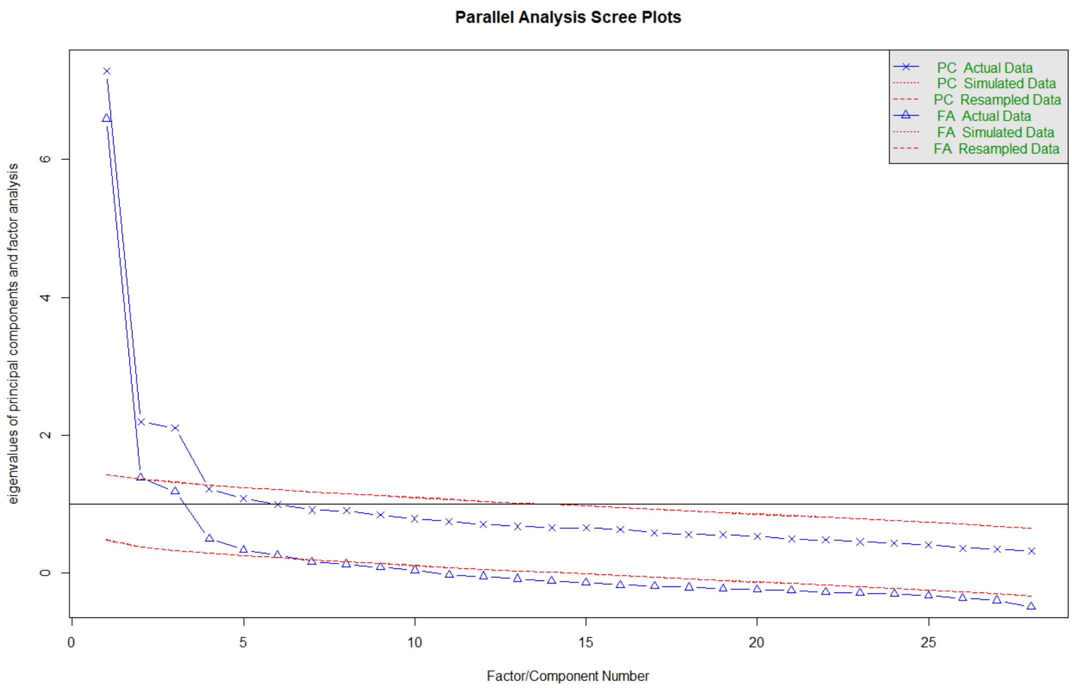


Figure 22: Scree plot EFA Four-Factor Orthogonal Model

In conducting the CFA, 26 variables were retained. Within this analysis the goodness of fit statistics of the EFA Four-Factor Orthogonal Model: $\chi^2 = 836.586$; df = 291; $p < .001$; $\chi^2/df = 2.875$; RMSEA = 0.051; RMSEA CI_{90} = 0.055; SRMR = 0.059; CFI = 0.896; NFI = 0.85; AGFI = 0.902; AIC = 68 197.88 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although CFI and NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Four-Factor Orthogonal Model were above 0.453 (Appendix E: Instrument Validation). Within the analysis, four items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28; Q_24 ~~ Q_27. Latent variables were measured to covary specifically: Structure ~~ Support = 0.708; Structure ~~ Independence = 0.009; Structure ~~ Resources = 0.51; Support ~~ Independence = -0.06; Support ~~ Resources = 0.749; Independence ~~ Resources = 0.03 (Figure 23). The modification index indicated no more covariances to consider with MI > 49. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.62, alpha > 0.6). However, AVE scores were typically < 0.48, suggesting similar issues with convergent and discriminant validity as previously reported (Table 27).

Table 27: CFA factor loadings and reliability EFA Four-Factor Orthogonal Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.79	0.80	0.33	Q_01	1.05	0.06	16.55	0	1.05	0.61	0.76
				Q_02	0.99	0.06	15.88	0	0.99	0.59	0.76
				Q_03	0.99	0.06	17.58	0	0.99	0.64	0.76
				Q_05	1.05	0.06	16.64	0	1.05	0.61	0.76
				Q_08	0.60	0.05	12.55	0	0.60	0.48	0.78
				Q_13	1.11	0.06	18.82	0	1.11	0.67	0.76
				Q_15	0.89	0.06	15.00	0	0.89	0.56	0.77
				Q_40	0.85	0.07	11.80	0	0.85	0.45	0.79
Support	0.85	0.85	0.34	Q_12	0.90	0.05	18.25	0	0.90	0.64	0.83
				Q_17	1.04	0.05	19.25	0	1.04	0.67	0.84
				Q_24	0.84	0.05	17.24	0	0.84	0.61	0.84
				Q_27	0.86	0.06	15.58	0	0.86	0.57	0.84
				Q_28	0.88	0.05	16.44	0	0.88	0.59	0.84
				Q_32	0.72	0.05	14.98	0	0.72	0.55	0.84
				Q_37	0.78	0.06	13.99	0	0.78	0.52	0.84
				Q_44	0.88	0.06	15.06	0	0.88	0.55	0.84
				Q_47	0.86	0.05	16.83	0	0.86	0.60	0.84
				Q_49	0.77	0.06	12.46	0	0.77	0.47	0.85
				Q_50	1.11	0.07	16.85	0	1.11	0.60	0.84
Independence	0.60	0.62	0.30	Q_04	0.97	0.09	10.88	0	0.97	0.49	0.55
				Q_09	1.26	0.09	14.11	0	1.26	0.68	0.45
				Q_16	0.99	0.09	11.02	0	0.99	0.50	0.56
				Q_22	0.85	0.08	10.73	0	0.85	0.49	0.54
Resources	0.75	0.73	0.48	Q_33	1.13	0.08	14.01	0	1.13	0.54	0.75
				Q_34	1.42	0.07	20.72	0	1.42	0.75	0.64
				Q_36	1.66	0.08	21.62	0	1.66	0.77	0.59

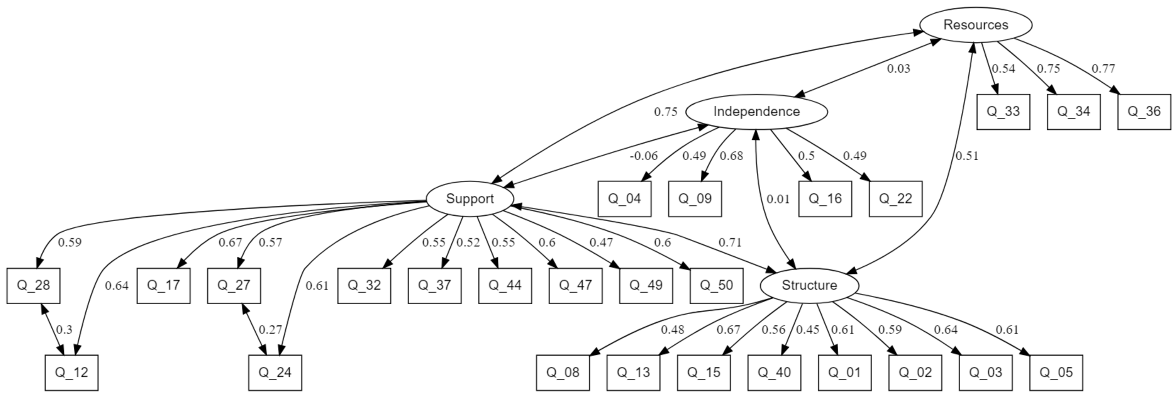


Figure 23: CFA factor loadings EFA Four-Factor Orthogonal Model

5.2.3.6. EFA Four-Factor Oblique Model

The sixth model is represented by four factors, utilising an oblique rotation. The four-factor analysis was conducted with Direct Oblimin rotation, where 25 variables were ultimately retained. Bartlett's test suggested that the correlation matrix was significantly different from an identity matrix χ^2 (300) = 4 156.704, $p < .001$. The overall KMO measure was 0.89. The KMO of the individual retained variables was consistently > 0.7, above the suggested 0.5 cut-off (Field et al., 2012; Rui Sarmento & Costa, 2019; Yong & Pearce, 2013; Zygmont & Smith, 2014), whereas the determinant was measured at 0.0008189387. A parallel analysis indicated that six factors or three components needed to be retained. There were three factors that presented an eigenvalue above one, whereas the scree plot demonstrated a possible four-factor structure (Figure 24), suggesting that the number of factors would be adequate for this analysis. SS loadings were MR1 = 3.81, MR2 = 1.44, MR3 = 2.16, and MR4 = 1.93, whereas the EFA explained a total of 37% of the variance. Loadings within this iteration were above 0.4, and variable commonalities were above 0.18. Factors could be identified as: Structure; Support; Independence; and Resources, and reflected the theoretical framework. However, some variables seemed to be more strongly related to the factors within which it was not originally conceptualised (see Appendix E: Instrument Validation). Item comparisons are expanded on within the section summary (section 5.2.4).

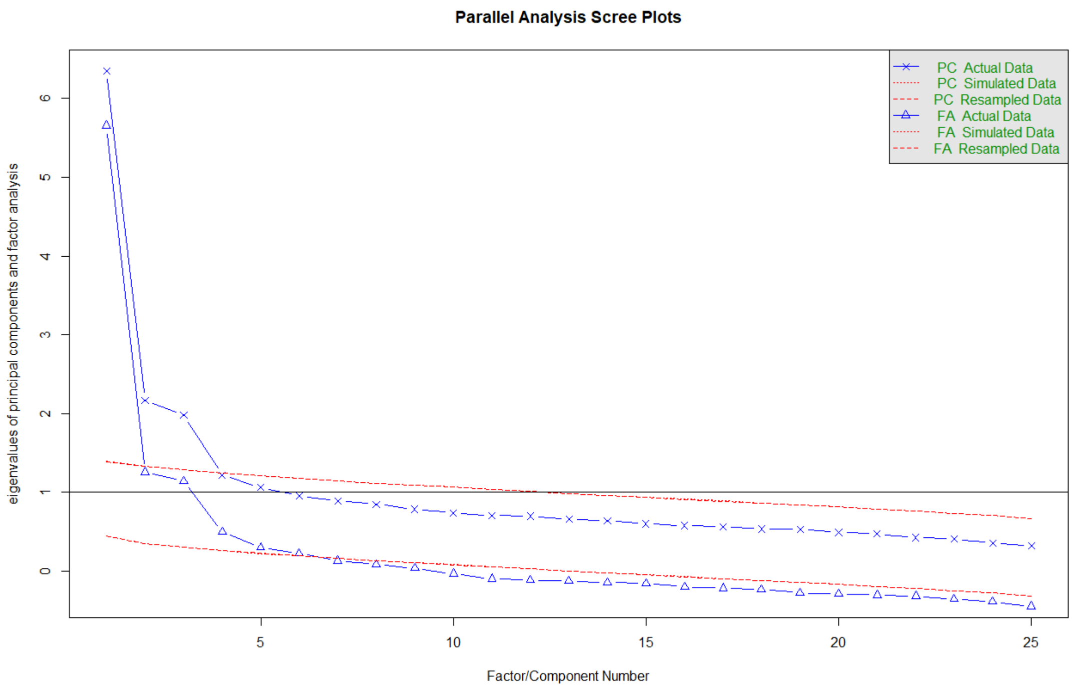


Figure 24: Scree plot EFA Four-Factor Oblique Model

In conducting the CFA, 24 variables were retained. Within this analysis the goodness of fit statistics of the EFA Four-Factor Oblique Model: $\chi^2 = 663.445$; df = 245; $p < .001$; $\chi^2/df = 2.708$; RMSEA = 0.048; RMSEA CI_{90} = 0.053; SRMR = 0.056; CFI = 0.907; NFI = 0.861; AGFI = 0.913; AIC = 63 107.38 (Table 29). Model fit implied that the current version of the model could be considered adequate for this project, although NFI scores were lower than the desired thresholds. The standardised factor loadings for the EFA Four-Factor Oblique Model were above 0.43 (Appendix E: Instrument Validation). Within the analysis, two items' error variances were allowed to covary to improve model fit: Q_12 ~~ Q_28. Latent variables were measured to covary specifically: Structure ~~ Support = 0.63; Structure ~~ Independence = 0.035; Structure ~~ Resources = 0.453; Support ~~ Independence = -0.063; Support ~~ Resources = 0.725; Independence ~~ Resources = 0.03 (Figure 25). The modification index indicated no more covariances to consider with MI > 49. The CR and alpha measurement of the model indicated that latent variables tended to be reliable (CR > 0.62, alpha > 0.6). However, AVE scores were typically < 0.48, suggesting similar issues with convergent and discriminant validity, as previously reported (Table 28).

Table 28: CFA factor loadings and reliability EFA Four-Factor Oblique Model

Latent variables:	Alpha	CR	AVE	Item	Estimate	SE	z-value	P(>|z|)	Std.lv	Std.all	Alpha if removed
Structure	0.75	0.76	0.35	Q_01	1.03	0.07	15.67	0	1.03	0.59	0.70
				Q_02	1.09	0.06	17.48	0	1.09	0.65	0.69
				Q_03	1.07	0.06	18.69	0	1.07	0.69	0.70
				Q_05	1.08	0.07	16.77	0	1.08	0.63	0.69
				Q_08	0.63	0.05	12.99	0	0.63	0.50	0.73
				Q_40	0.81	0.08	10.85	0	0.81	0.43	0.75
Support	0.85	0.84	0.33	Q_12	0.87	0.05	17.58	0	0.87	0.63	0.83
				Q_14	0.78	0.06	12.79	0	0.78	0.48	0.84
				Q_17	1.06	0.05	19.71	0	1.06	0.68	0.83
				Q_24	0.89	0.05	18.65	0	0.89	0.65	0.83
				Q_27	0.93	0.05	17.20	0	0.93	0.61	0.83
				Q_28	0.85	0.05	15.75	0	0.85	0.57	0.83
				Q_32	0.71	0.05	14.63	0	0.71	0.54	0.83
				Q_37	0.78	0.06	13.83	0	0.78	0.51	0.84
				Q_44	0.85	0.06	14.54	0	0.85	0.53	0.83
				Q_47	0.87	0.05	17.02	0	0.87	0.61	0.83
				Q_49	0.74	0.06	11.89	0	0.74	0.45	0.84
Independence	0.60	0.62	0.30	Q_04	0.97	0.09	10.86	0	0.97	0.49	0.55
				Q_09	1.26	0.09	14.13	0	1.26	0.68	0.45
				Q_16	0.99	0.09	11.02	0	0.99	0.50	0.56
				Q_22	0.85	0.08	10.77	0	0.85	0.49	0.54
Resources	0.75	0.73	0.48	Q_33	1.13	0.08	13.91	0	1.13	0.54	0.75
				Q_34	1.43	0.07	20.78	0	1.43	0.75	0.64
				Q_36	1.64	0.08	21.26	0	1.64	0.77	0.59

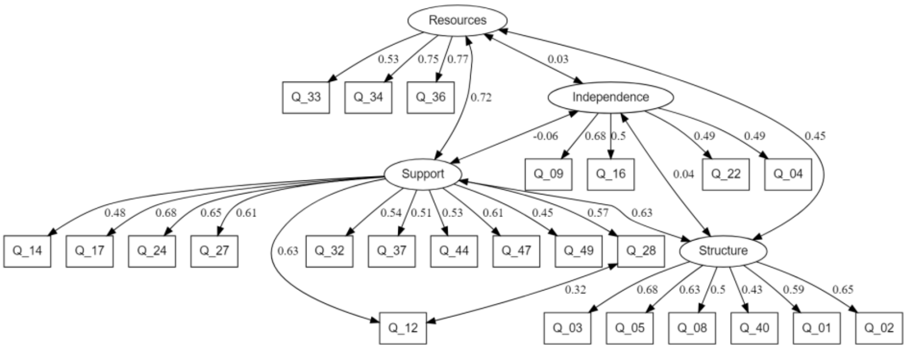


Figure 25: CFA factor loadings EFA Four-Factor Oblique Model

5.2.4. Summary of EFA models

Six alternative models were explored within the EFA to improve the CFA models presented in the first part of the chapter. The EFA highlighted that up to four latent factors could be distinguished from various combinations of 21-26 variables viewed in either orthogonal or oblique factor rotations. Similar to the proposed theoretical framework, two latent variables could be identified as Structure and Support. Variables initially designed to have negative loadings formed a third factor that could be identified as Independence, which was unrelated to any other presented factors. The fourth factor within this analysis was identified as additional Resources, which consisted of variables that formed part of the Support factor when fewer factors were extracted. Each model was tested through a CFA with a larger sample set, and model fit statistics are presented below to serve as comparisons.

The goodness of fit statistics for each CFA iteration was presented earlier and, for the most part, displayed scores within the acceptable ranges adopted within this study. However, the NFI for all the CFA iterations were below the desired thresholds, whereas the CFI for one of the models did not reach the desired cut-off. The SRMR and the AIC scores indicated that the two-factor models would have been more appropriate for this study (Table 29), both presenting factors that could be interpreted as Structure and Support, consistent with the study's theoretical framework. This study's standardised factor loadings exceeded the adopted cut-off (0.4). Although lower than the suggested 0.5 (Awang, 2012; Hair et al., 2014), it was nonetheless argued to be sufficient for the exploratory nature of this project.

Table 29: EFA Model CFA goodness of fit

Model Code *	EFA Two-Factor Orthogonal Model	EFA Two-Factor Oblique Model	EFA Three-Factor Orthogonal Model	EFA Three-Factor Oblique Model	EFA Four-Factor Orthogonal Model	EFA Four-Factor Oblique Model	Cut-off
Factors	2	2	3	3	4	4	-
Items	22	21	26	24	26	24	-
χ^2	623.213	494.315	792.092	627.576	836.586	663.445	See p-value
Df	205	185	293	246	291	245	-
Sig	0	0	0	0	0	0	P > 0.05 **
χ^2/df	**3.04**	**2.672**	**2.703**	**2.551**	**2.875**	**2.708**	Mediocre (2-5)
RMSEA	**0.053**	**0.048**	**0.048**	**0.046**	**0.051**	**0.048**	Good (0.05 – 0.08)
RMSEA CI_{90}	**0.058**	**0.053**	**0.052**	**0.051**	**0.055**	**0.053**	Good (0.05 – 0.08)
SRMR	**0.05**	**0.044**	0.055	0.056	0.059	0.056	Good (< 0.05)
CFI	**0.91**	**0.93**	**0.9**	**0.917**	0.896	**0.907**	Good (0.9 – 0.95)
NFI	0.872	0.893	0.851	0.871	0.85	0.861	Good (0.9 – 0.95)
AGFI	**0.91**	**0.923**	**0.907**	**0.918**	**0.902**	**0.913**	Standard (AFGI > 0.90)
AIC	56 381.657	**53 671.584**	68 001.768	62 852.425	68 197.876	63 107.384	Lower value indicates better fit

* Raw outputs are available in Appendix E: Instrument Validation.

** Significance on all models can be expected due to the sample size.

Similar to the previously conducted CFA, variable errors were only specified to covary if such combinations were consistent with the presumed factor combinations as presented in the EFA. Only the four question combinations as were described previously were allowed to covary. The reliability of the six models was above the desired thresholds for both CR and Cronbach's alpha scores. However, lower AVE scores indicated a similar convergent and discriminant validity problem as presented within previous CFA models.

Question loadings were investigated to consider possible response patterns. Overall, 21 questions were not included in any model (Table 30). Excluded questions would cover a range of reasons, including double-barrelled meanings, and questions that may have been phrased in a way that encourages bias (such as Q_41 discussed in section 5.1). Removal of such questions would thus presumably reduce the measurement error within this project.

Table 30: Excluded questions

Factors	Items	
Structure	Q_07	Q_21
	Q_10	Q_23
	Q_11	Q_25
	Q_18	Q_26
	Q_19	Q_30
	Q_20	
Support	Q_35	Q_43
	Q_38	Q_45
	Q_39	Q_46
	Q_41	Q_48
	Q_42	Q_51

A total of 30 questions were utilised across the six EFA models. It is important to note that although not all the variables loaded strongly enough to be retained in every model, each variable was only associated with a single underlying factor structure across the analysis iterations (Table 31). Similar factor structures could be identified within the EFA, as presented in the theoretical framework. However, some variables did not associate in the anticipated way. An example of such cross-loading was Q_12 "Supervisors should assist their students to get involved in relevant conferences and colloquiums”. The question was created to form part of the organisational aspect of structure within the supervision relationship; however, it seemed to be more related to Supportive questions within the analysis. Considering the question wording, principally from the student’s perspective, such loadings would make sense. From a student’s perspective, conferences may not be interpreted as an aspect of learning that supervisors are responsible for providing access to. Instead, taken as gratitude that supervisors signify their interest in students’ work by providing additional support by assisting their students to get involved in conferences and colloquiums.

Similarly, questions that ultimately loaded on the latent factor Independence were created to indicate whether students did not need high levels of Structure or Support (envisioned initially to be reverse scored). Instead, students’ responses seemed to indicate a third possible latent factor unrelated to structure or support. This may mean that students interpreted questions related to Independence as ownership of their work rather than needing less supervisor involvement. Alternatively, students may strive toward greater independence from their supervisors as their studies progress (Jones, 2013). A similar finding was made by Herrmann and Wichmann-Hansen (2017), where the authors argued that students might find it self-evident that they need to make critical decisions on their projects. Related to Independence, Mouton et al. (2015) incorporated questions connecting the locus of decisions or Independence within their analysis of supervision relationships. Where their inclusion was also within the Structural factor, the findings presented here suggest that Independence, at least perceived by students, may be completely separate from their Structure needs. However, it may be included in master’s and doctoral education research, as Fleming et al. (2013) suggest.

Table 31: Retained questions

Items	EFA Two-Factor Orthogonal Model	EFA Two-Factor Oblique Model	EFA Three-Factor Orthogonal Model	EFA Three-Factor Oblique Model	EFA Four-Factor Orthogonal Model	EFA Four-Factor Oblique Model
Q_01	St	St	St	St	St	St
Q_02	St	St	St	St	St	St
Q_03	St	St	St	St	St	St
Q_04	-	-	Ind	Ind	Ind	Ind
Q_05	St	St	St	St	St	St
Q_06	St	St	St	St	-	-
Q_08	St	St	St	St	St	St
Q_09	-	-	Ind	Ind	Ind	Ind
Q_12	Su	Su	Su	Su	Su	Su
Q_13	St	-	St	-	St	-
Q_14	-	-	-	-	-	Su
Q_15	St	-	St	-	St	-
Q_16	-	-	-	Ind	Ind	Ind
Q_17	-	Su	-	Su	Su	Su
Q_22	-	-	Ind	Ind	Ind	Ind
Q_24	Su	Su	Su	Su	Su	Su
Q_27	Su	Su	Su	Su	Su	Su
Q_28	Su	Su	Su	Su	Su	Su
Q_29	-	-	Ind	-	-	-
Q_31	Su	Su	Su	Su	-	-
Q_32	Su	Su	Su	Su	Su	Su
Q_33	Su	Su	Su	Su	Res	Res
Q_34	Su	Su	Su	Su	Res	Res
Q_36	Su	Su	Su	Su	Res	Res
Q_37	Su	Su	Su	-	Su	Su
Q_40	-	-	-	-	St	St
Q_44	Su	Su	Su	Su	Su	Su
Q_47	Su	Su	Su	Su	Su	Su
Q_49	Su	Su	Su	Su	Su	Su
Q_50	Su	Su	Su	Su	Su	-

St (Structure), Su (Support), Ind (Independence), Res (Resources)

5.3. Conclusion

This chapter considered the validity and reliability of the instrument utilised to measure Structure and Support as aspects of the supervision relationships. This purpose responds to the first research question: “Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?” Consistent with the critique by Borsboom et al. (2004), the instrument designed for this study was developed from a theoretical perspective. It was presumed that supervision relationships were measurable, and that Gatfield's (2005) conceptualisation of supervision would be appropriate given that several frameworks shared similar traits. This chapter outlined a total of ten possible models of such a measurement. The four models presented at the beginning of the chapter presented a baseline model for a two-factor and a six-factor model directly derived from the theoretical framework. Due to the difficulties of operationalising supervision relationships, it was necessary to explore alternative models to those presented in the CFA (Wichmann-Hansen & Herrmann, 2017). The EFA analysis presented six possible alternative models, conceptualising two-factor, three-factor, and four-factor models with orthogonal and oblique rotations. The alternative models reflected aspects of the theoretical framework, where latent factors relating to Structural and Supportive elements were identifiable throughout the analysis (Figure 26).

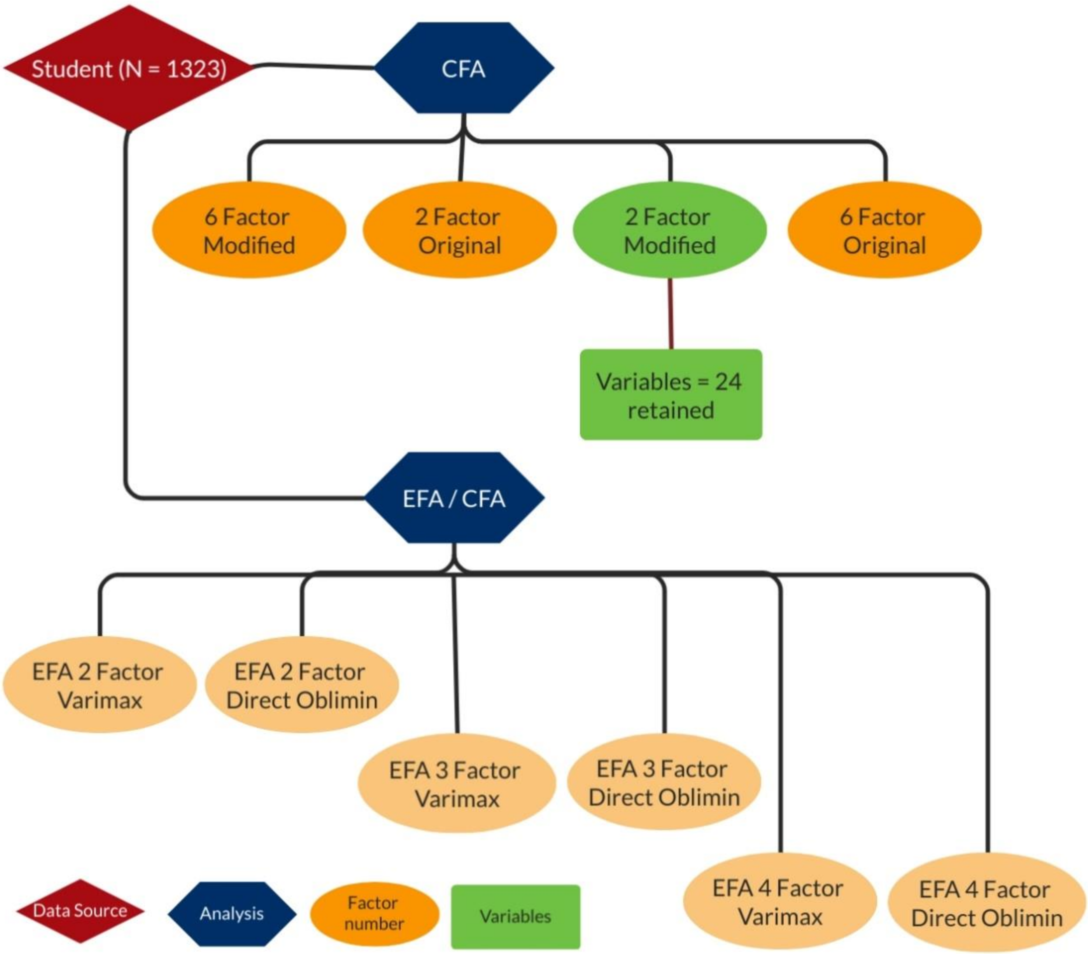


Figure 26: Validity - factor analysis summary

Source: Author (Visme)

In choosing an appropriate model as the basis for the study, two primary considerations were taken into account. The instrumentalist argument studies the statistical loadings of different factors, and the theoretical approach reflects on the foundation of the analysis. According to an instrumentalist view, each model displayed acceptable fit statistics. However, fit statistics were slightly improved for the adapted CFA models: RMSEA and SRMR scores were typically slightly lower. In addition, CFI, NFI, and AGFI scores were typically slightly higher for the adapted CFA models compared to the models designed from EFA results. However, the six-factor CFA model contained two factors that relied on only two variables each, which may be inappropriate for acting as a measurement tool. Therefore, the model that seemed to provide the best representation of the threshold requirements of the analysis was the two-factor CFA model. The identified two-factor model additionally showed good Cronbach's alpha reliability on the supervisor measurement for Structure (α= 0.86) and Support (α = 0.81). It should be noted that each model contained reliable factors, however, displayed problems with convergent and divergent validity, due to lower AVE scores. This observation prompts the need for theoretical justification for the utilisation of the instrument.

A theoretical perspective needs to consider why such an analysis is conducted. The study utilised CFA and EFA techniques in order to discover possible response patterns that suggest underlying constructs can be utilised as measurements of supervision relationships. However, the theoretical approach used as a foundation for this study presents supervision relationships as a whole (not from a single perspective), which was not possible within the collected data for this project. Instead, only the perspectives of students were presented. The study furthermore focused on the didactic relationship between supervisor and student, whereas the HEI forms a third party that strongly influences supervision practices. This additional connection was not considered within this project so as to ensure that focus can remain on the supervision relationship itself.

Furthermore, from the perspective of students, the inclusion of the relationship with the HEI may not be directly relevant. Students typically connect or interact with their HEI through supervisors, who act as a central contact point within the institution. Thus, students may not be aware of how strongly the institution influences their academic experiences, particularly within an ODeL institution. As a result, it would make sense that questions were cross-loaded within the CFA and EFA analysis. It is necessary to reiterate that such loadings were consistent throughout the analysis.

As a result, it was determined that the initial modified two-factor CFA model (CFA Two-Factor Modified Model) would be the most appropriate measurement of supervision relationships within this study. This model would have a stronger basis in the theoretical approach, which considers supervision as a whole, but was adapted from the student's perspective. Students may not think of structural acts as part of their educational requirements, but this does not change the nature or function of such activities. Utilising the CFA Two-Factor Modified Model (Figure 54) thus ensures that the theoretical approach drives the measurement process within this study. However, variables that may have increased the measurement error, or noise, within this project were removed, based on student experiences.

Future iterations of projects that measure supervision relationships in such a way could consider possible improvements to the presented instrument. Limiting response options to five instead of seven options may provide a more transparent alternative for both students and supervisors. Removal of the question randomisation may address convergent and divergent validity issues. Whereas clarifying the wording on problematic items and avoiding reverse-scored items may improve the measurement instrument. Albeit possibly create additional difficulties in the measurement process. The concept of Independence may be an area for further investigation (Jones, 2013) that can be argued to form part of the exogenous variables in Gatfield's (2005) model. Finally, considering respondents' response behaviour through other analytical methods, such as item response theory (IRT), may provide a different perspective.

The following chapter presents the results of the analysis of the research findings. The data analysis for this project was based on the aggregation of the Structure and Support items, as outlined within the selected model. The aggregation was made for both student and supervisor data, given that the data from both groups displayed good reliability scores. The results chapter thus presents the findings relevant to answering the remaining three research questions.

Chapter 6: Results

The previous chapter responded to the first research question, where the psychometric properties of the supervision fit scales were outlined. Ultimately the adapted two-factor model was adopted, representing the original theoretical model, albeit from the student's perspective. The following chapter provides an overview of the results gathered from student and supervisor surveys (the supervision style indices: Structure and Support) and the linked institutional data to address the remaining three research questions. The chapter is structured so as to respond to the remaining research questions within three distinct discussion sections (Table 32).

The first section will address the results gathered from the student survey. Descriptive statistics are provided on the sample characteristics and measures of the central tendency of students' time to completion and their supervision style preferences. Students' preferred supervision styles and time to completion are compared in order to investigate possible differences between master's and doctoral students, responding to the second research question using nonparametric statistics (Table 32).

The chapter's second section discusses the findings from the supervisor survey. Similar to the first section, descriptive statistics are provided on the characteristics of the supervision sample, as well as measures of central tendency for the supervision style preferences of supervisors. These preferences were compared across various supervision characteristics through parametric and nonparametric statistics. Thus, investigating possible differences between supervisors' preferences resulting from various contextual or personal factors to address the third research question (Table 32).

The final section addresses the fourth research question regarding the relationship between supervision fit and the time to completion of students (Table 32). The student data was combined with the data available from their supervisors to compare the difference in their supervision preference scales (presumed to reflect congruence within their relationships) and the time to completion of students. This addresses the research purpose, relating to the relationship between student-supervisor fit and time to completion of students in master's and doctoral education.

Table 32: Research questions overview

Research question	Section	Sample size
RQ 2: Is there a difference between the supervision style preferences of master's and doctoral students?	6.1 Student	Student sample: 1 183
RQ 2.1: Is there a relationship between the supervision style preferences of master's and doctoral students and their time to completion?		Student sample who completed their studies: 578
RQ 3: Which factors influence the supervision style preferences of master's and doctoral supervisors?	6.2 Supervisor	Supervisor sample: 169
RQ 4: Is there a relationship between the congruence of supervision relationships and the time to completion of master's and doctoral students?	6.3 Supervision relationship	Student-supervisor dyads total: 137 Dyads where the student completed their studies: 69

6.1. Student

As was previously presented, after data cleaning, a total of 1 323 unique student responses were recorded and used in the validation and reliability check of the research instrument. The results section merged individual students' records with the students' data obtained from the Unisa student information systems. In total, 1 183 student records were linked to the survey respondents who submitted the online survey. A slightly reduced sample was the source of the current analysis, primarily due to the prioritising of linking students with institutional data for the analysis. After the descriptive overview of the student respondents, comparisons are made to explore differences or relationships between various student characteristics and their time to completion or supervision style preferences.

6.1.1. Student sample description

Within this study, most of the respondents were registered for a master's qualification (n = 757; 64%), compared to those registered for doctoral qualifications (n = 426; 36%). When the institutional data was requested, just under half of the student respondents (n = 578; 49%) had completed their studies for a particular qualification. The majority of those respondents completed a master's level qualification (n = 423; 73%), and about a quarter of the respondents completed a doctoral qualification (n = 155; 27%). Of the remaining half of the respondents who had not completed their studies at the time (n = 605; 51%), students were registered at a master's (n = 334; 55%) and doctoral (n = 271; 45%) qualification level (Table 33).

Table 33: Student completion by degree level

Variables	Response	Complete		Incomplete		Total	
		n	%	n	%	n	%
Qual Type	Master's	423	73%	334	55%	757	64%
	Doctoral	155	27%	271	45%	426	36%
Dataset	Completion status	578	49%	605	51%	1 183	100%

In considering the qualification characteristics of respondents who had completed their qualifications, the majority of the master's graduates completed a full research master's (n = 256; 61%), as opposed to a master's of limited scope[44] (n = 167; 39%). All the doctoral graduates within this sample completed a full research qualification (n = 155). Respondents completed their qualifications within the three-year period specified during the sampling framework, namely, 2017 (n = 102; 18%), 2018 (n = 158; 28%), 2019 (n = 221; 39%), as well as the year when the data was requested; 2020 (n = 93; 16%) (Table 34).

Table 34: Student qualification type and completion year by degree level

Variable	Response	Completed					
		M	M%	D	D%	Total	Total%
Qual Research Type	Full research	256	61%	155	100%	411	71%
	Limited scope	167	39%	0	0%	167	29%
	Total	423	100%	155	100%	578	100%
Completed*	2017	80	19%	22	14%	102	18%
	2018	122	29%	36	23%	158	28%
	2019	152	36%	69	45%	221	39%
	2020	66	16%	27	18%	93	16%
	Total	420	100%	154	100%	574	100%

* Four of the listed respondents did not have a completed year recorded at the time of data collection.

[44] Master's of limited scope is typically a professional master's qualification that includes coursework as part of the training. Thus, the intensity of the research component is typically reduced for such qualifications (see Section 2.1).

Overall, respondents' characteristics were typically similar for those who completed their studies, when compared to respondents whose studies were not completed. Differences across completion status can be referred to in Table 35. Most respondents indicated that they lived in South Africa (n = 803; 68%), and the largest group lived in the Gauteng Province (n = 506; 43%), where the Unisa main campus is located. The remaining 25% of the respondents indicated that they lived in one of the other eight provinces (the distribution ranged between 0.5% and 6%). Just under a third of the respondents indicated that they lived outside the borders of South Africa (n = 377; 32%) (Table 35).

Most of the respondents were employed full-time (n = 908; 77%) or on a part-time basis (n = 127; 11%) at the time of the survey. A minority of the respondents indicated that they were on contracts or self-employed (n = 12; 1%); retired (n = 6; 0.5%); unemployed (n = 13; 1.1%); or other (n = 5; 0.4%). Overall, just over one hundred respondents were full-time students when the data was collected (n = 110; 9%) (Table 35).

Respondents indicated that they were typically allocated a supervisor for their studies when they applied through their departments (n = 796; 67%), although some of the respondents spoke to potential supervisors beforehand (n = 284; 24%). A few respondents indicated that their supervisors were recommended by someone (n = 83; 7%), whereas a minority of the current sample seemed to have been at the start of their master's or doctoral studies without having been allocated a supervisor (n = 8; 1%); or selected other (n = 7; 1%) (Table 35).

The largest groups of respondents were registered in the College of Human Sciences (n = 406; 34%), whereas the Colleges of Economic and Management Sciences (n = 182; 15%); Education (n = 132; 11%); Graduate School of Business Leadership (n = 131; 11%); Science, Engineering and Technology (n = 119; 10%); and Agriculture and Environmental Sciences (n = 118; 10%) each comprised of 10% or more of the sample. The three smallest colleges represented in this sample were: Graduate Studies (n = 34; 3%); Law (n = 33; 3%); and Accounting Sciences (n = 19; 2%) (Table 35).

Most of the respondents funded their own studies (n = 611; 52%), whereas the second largest group indicated that their studies were funded through a bursary (n = 363;

31%). This was followed by the respondents whose employers had funded their education (n = 136; 12%). Smaller groups of respondents indicated that their studies were funded through multiple sources (n = 35; 3%), families (n = 23; 2%), or other (n = 12; 1%) (Table 35).

A minority of the respondents stated that they changed their supervisors throughout their studies (n = 122; 10%). Compared to the majority of respondents who had not changed supervisors (n = 1 058; 90%) (Table 35).

Table 35: Student characteristics

Variables	Response	Complete		Incomplete		Total	
		n	%	n	%	n	%
Reside SA	Yes	392	68%	411	68%	803	68%
	No	184	32%	193	32%	377	32%
SA Province	Eastern Cape	15	3%	14	2%	29	3%
	Free State	6	1%	8	1%	14	1%
	Gauteng	247	43%	259	43%	506	43%
	KwaZulu-Natal	27	5%	42	7%	69	6%
	Limpopo	25	4%	30	5%	55	5%
	Mpumalanga	18	3%	16	3%	34	3%
	North West	15	3%	12	2%	27	2%
	Northern Cape	4	1%	2	0.3%	6	1%
	Western Cape	31	5%	25	4%	56	5%
Employment	Employed Full-time	453	78%	455	75%	908	77%
	Employed Part-time	65	11%	62	10%	127	11%
	Studying Full-time	42	7%	68	11%	110	9%
	Contract / Self employed	4	1%	8	1%	12	1%
	Retired	3	1%	3	1%	6	1%
	Unemployed	8	1%	5	1%	13	1%
	Other:	2	0.3%	3	0.5%	5	0.4%
Supervisor allocated	I applied through the department	387	67%	409	68%	796	67%
	I spoke to potential supervisor beforehand	140	24%	144	24%	284	24%
	I was recommended by someone	42	7%	41	7%	83	7%
	Not allocated yet	4	1%	4	1%	8	1%
	Other:	3	1%	4	1%	7	1%
College	Accounting Sciences	11	2%	8	1%	19	2%
	Agriculture & Environmental Sciences	45	8%	73	12%	118	10%

Variables	Response	Complete		Incomplete		Total	
		n	%	n	%	n	%
	Economic & Management Sciences	78	14%	104	17%	182	15%
	Education	59	10%	73	12%	132	11%
	Graduate School of Business Leadership	97	17%	34	6%	131	11%
	Graduate Studies	11	2%	23	4%	34	3%
	Human Sciences	188	33%	218	36%	406	34%
	Law	32	6%	1	0.2%	33	3%
	Science, Engineering & Technology	52	9%	67	11%	119	10%
Funding	Self	253	44%	358	59%	611	52%
	Employer	89	15%	47	8%	136	12%
	Family	10	2%	13	2%	23	2%
	Bursary or scholarship	197	34%	166	27%	363	31%
	Multiple sources	22	4%	13	2%	35	3%
	Other:	6	1%	6	1%	12	1%
Changed Supervisors	Yes	60	10%	62	10%	122	10%
	No	517	90%	541	90%	1 058	90%

The overwhelming majority of respondents indicated that they communicated[45] with their supervisors via email (n = 1 151; 97%), accounting for 39% of the total responses, whereas several respondents reported additional communication channels. Communication channels that were also frequently selected included one-on-one meetings (n = 440; 37%) accounting for 15% of the responses, calls to their private phones (n = 365; 31%); social messaging apps (e.g., WhatsApp, Viber) (n = 356; 30%), and calls to their work phones (n = 301; 25%), each accounting for more than 10% of the total responses. Communication channels that were utilised by smaller number of respondents included SMSs (n = 173; 15%), online meetings[46] (n = 105; 9%), and group meetings (n = 81; 7%), which also formed a smaller proportion of the total responses provided to this question (Table 36).

[45] Respondents were able to select multiple responses for this question. The focus in the analysis was on which communication channels were used by respondents rather than the frequency of the selected communication methods. The proportion of the overall communication methods are reported here to provide additional context.
[46] The survey was distributed before the COVID-19 pandemic, and the subsequent increase in popularity of online meeting channels.

Table 36: Communication channels used by students

Response	Complete		Incomplete		Total		
	n	%	n	%	n	%	Responses %
Email	563	97%	588	97%	1151	97%	39%
Group meetings	46	8%	35	6%	81	7%	3%
One-on-one meetings	237	41%	203	34%	440	37%	15%
Online meetings	50	9%	55	9%	105	9%	4%
Social messaging	201	35%	155	26%	356	30%	12%
SMS	109	19%	64	11%	173	15%	6%
Tel work	156	27%	145	24%	301	25%	10%
Tel private	206	36%	159	26%	365	31%	12%
Total respondents	578	-	605	-	1 183	-	100%

* n = 14 respondents were not yet allocated to a supervisor and thus did not use any communication channels.

* Respondents were able to select multiple options that were relevant to their academic journeys. 'Responses %' may not add up to 100% due to rounding.

Respondents were also asked to estimate how much time they could work on their studies each week. The student respondents indicated that they were typically able to spend less than 30 hours on their studies per week. Just over a quarter of the respondents spent up to nine hours per week (n = 327; 28%), whereas just under a third of the respondents spent between 10 and 19 hours (n = 382; 32%). Fewer respondents indicated they could spend between 20 and 29 hours on their studies (n = 272; 23%). The students who were able to spend more time studying per week seemed to be in the minority, where some of the respondents indicated that they spent between 30 and 39 hours (n = 107; 9%), and a few respondents reported that they were able to spend more than 40 hours on their studies (n = 88; 7%) (Table 37; Figures 27 – 30).

Table 37: Hours students spend on their studies per week

	Complete		Incomplete		Total	
Response	n	%	n	%	n	%
1-9 hours	118	20%	209	35%	327	28%
10-19 hours	192	33%	190	31%	382	32%
20-29 hours	145	25%	127	21%	272	23%
30-39 hours	60	10%	47	8%	107	9%
40 hours or more	60	10%	28	5%	88	7%
Total	578	100%	605	100%	1 183	100%

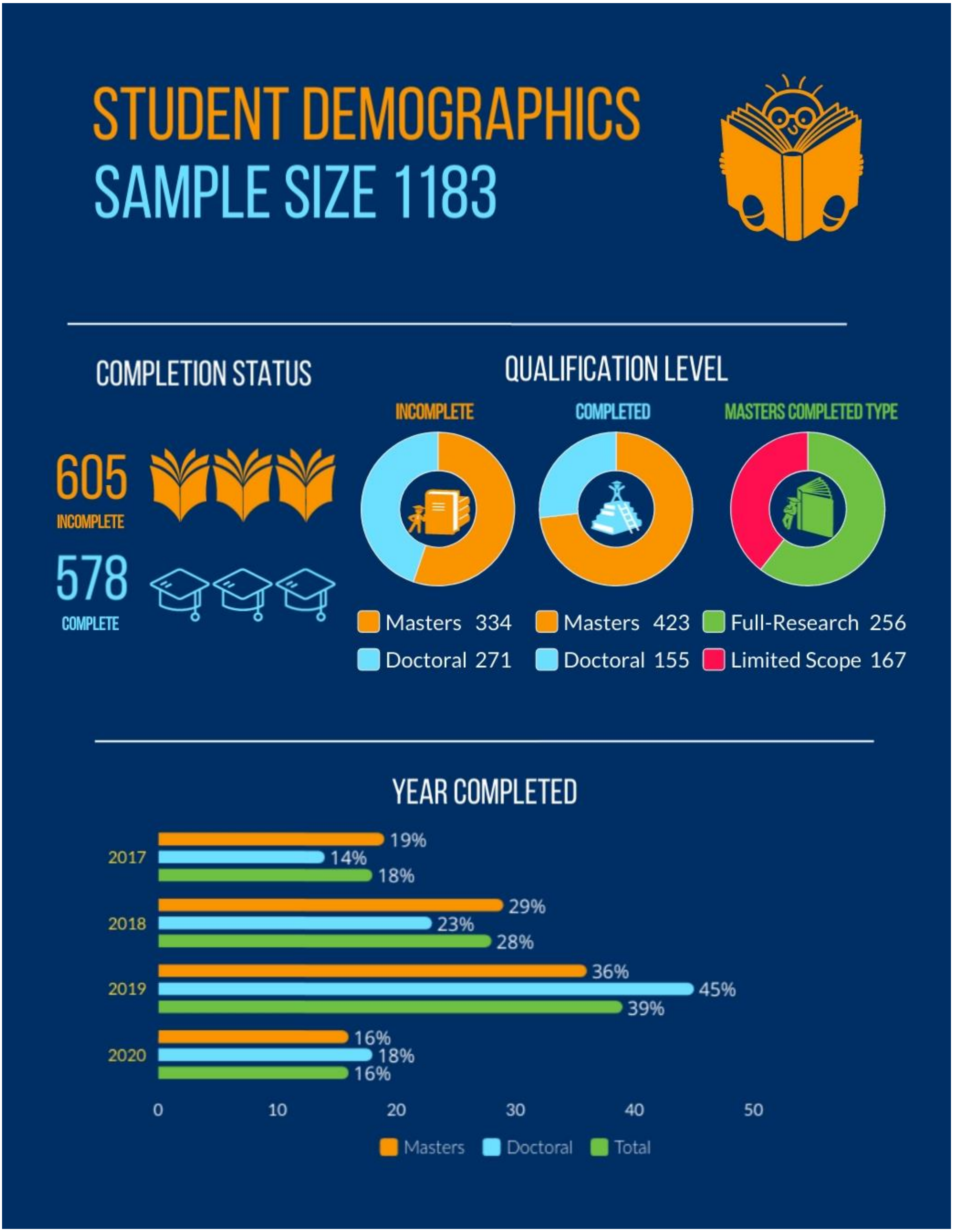


Figure 27: Descriptive statistics infographic (Student) 1/4

Source: Author (Visme)

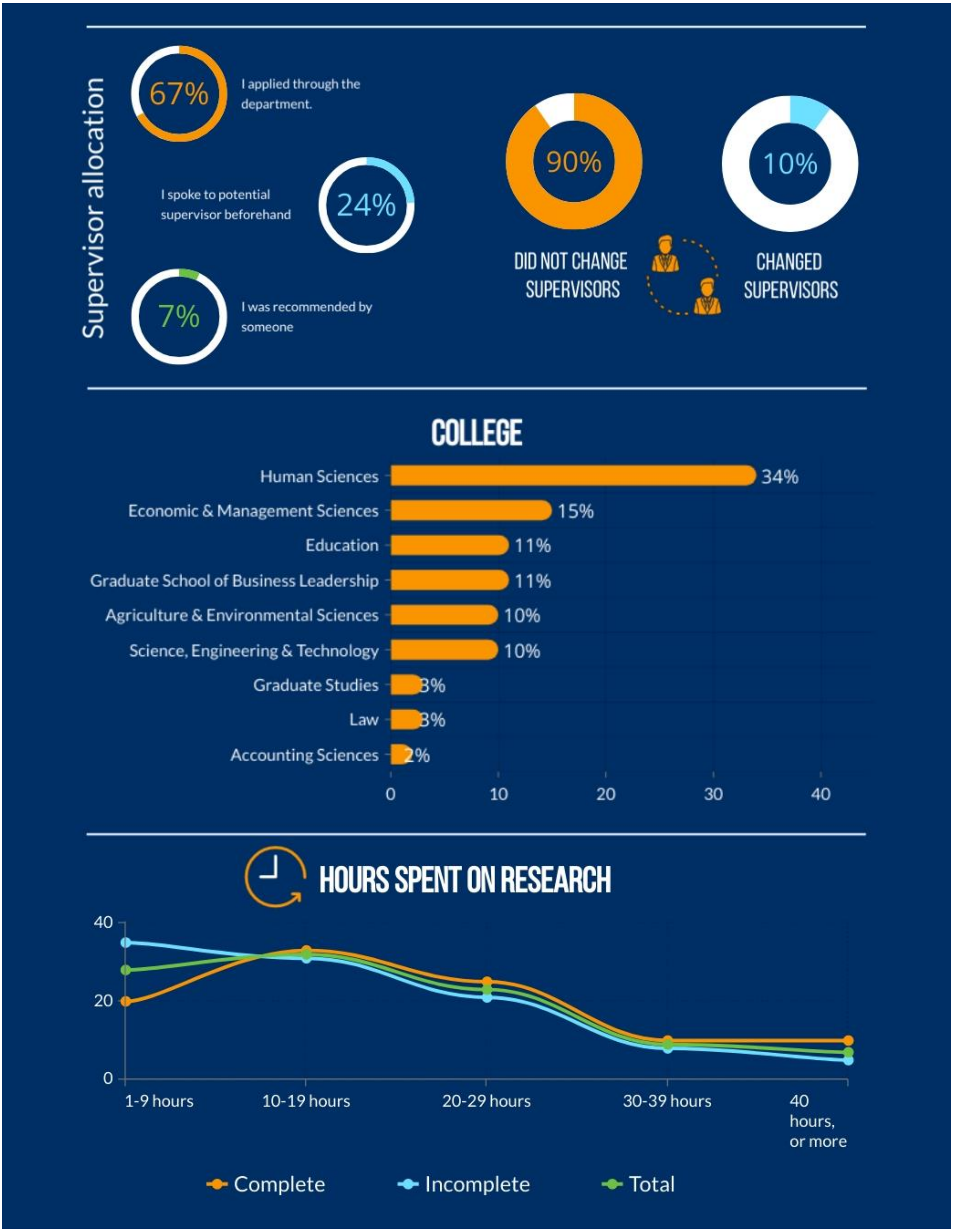


Figure 28: Descriptive statistics infographic (Student) 2/4

Source: Author (Visme)

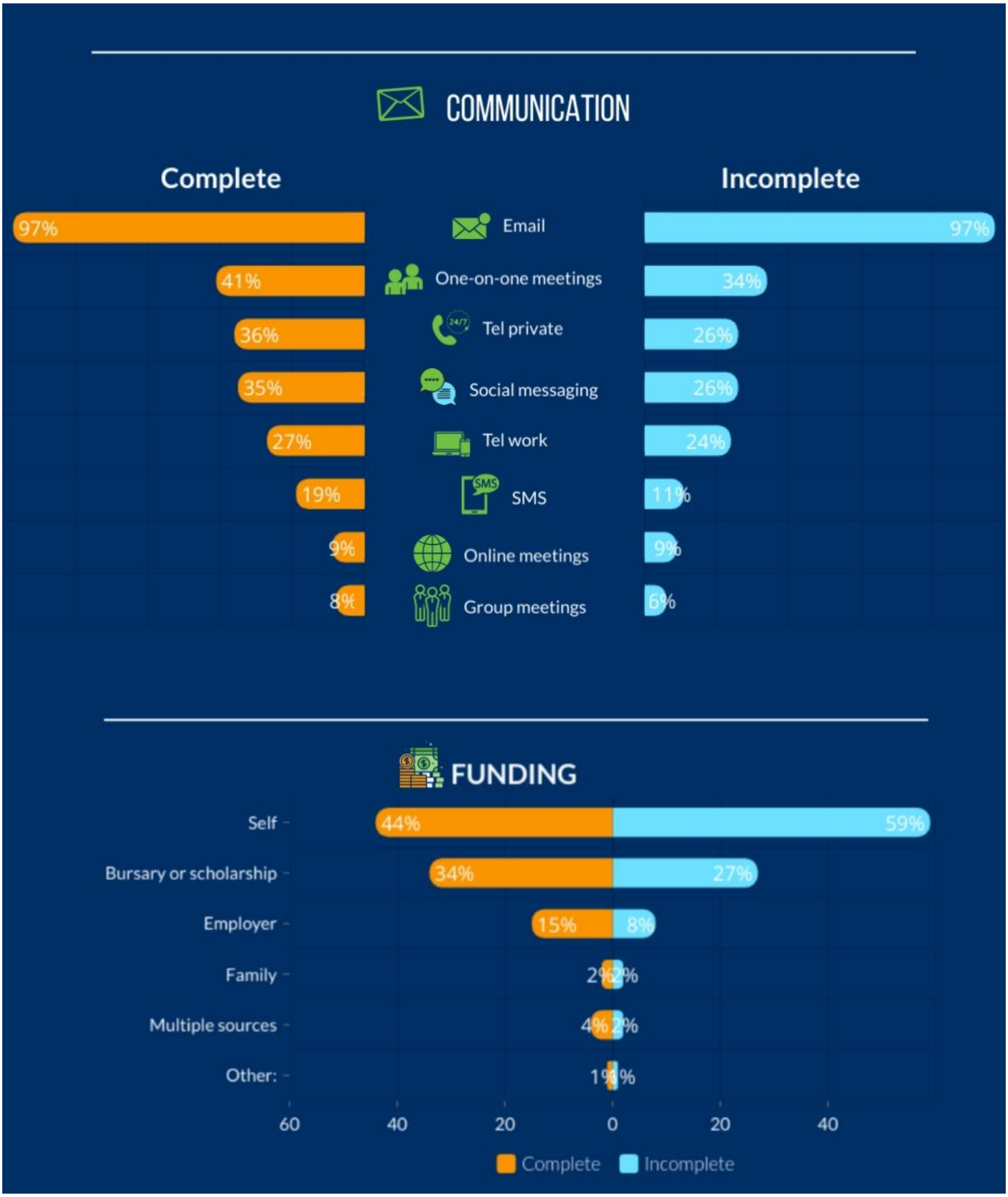


Figure 29: Descriptive statistics infographic (Student) 3/4

Source: Author (Visme)

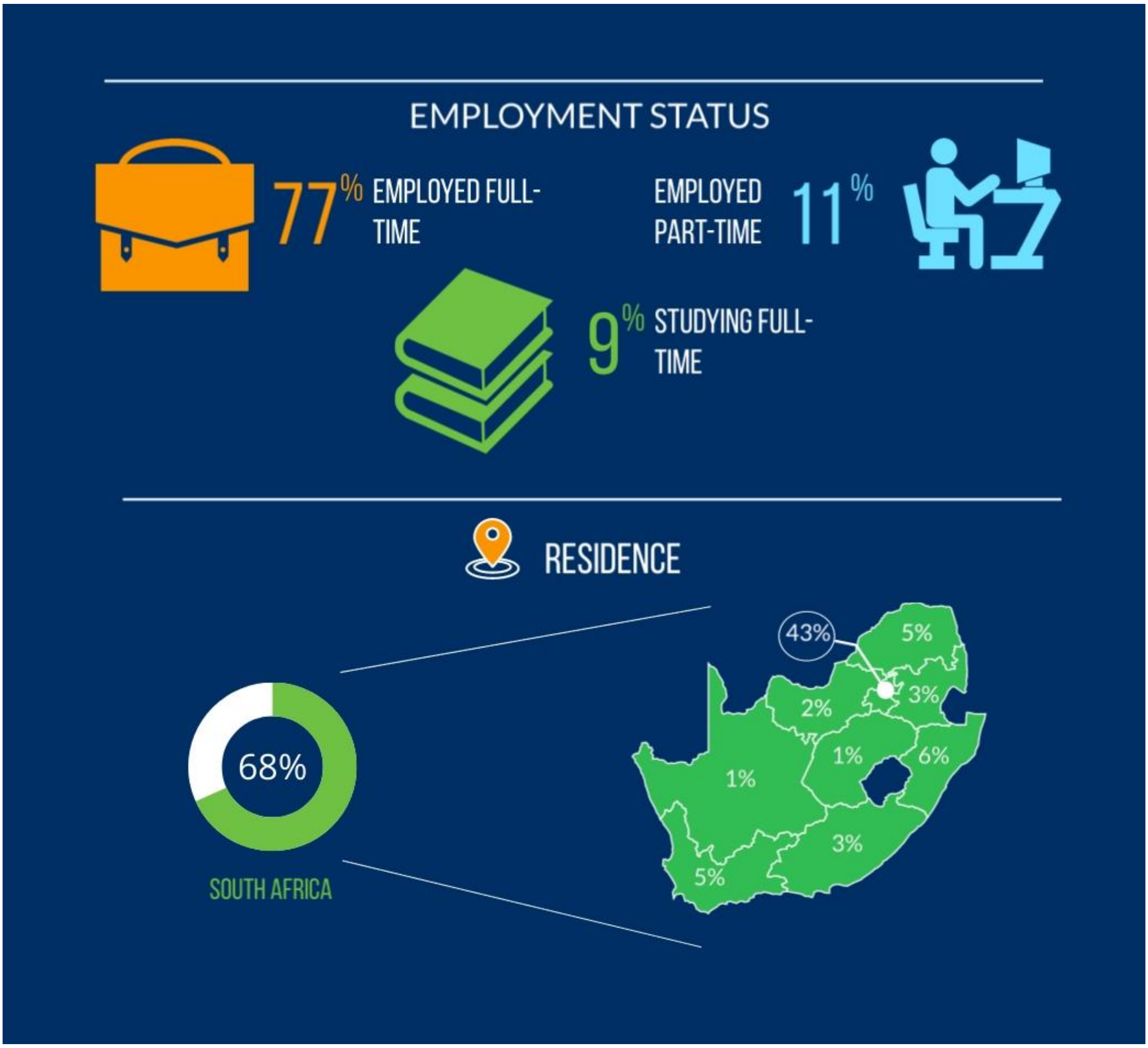


Figure 30: Descriptive statistics infographic (Student) 4/4

Source: Author (Visme)

6.1.2. Students' time to completion

As argued in the literature review chapter, students' completion time would be calculated by subtracting the first registration date for a qualification from the end date. The time to completion for students within this study was thus calculated by subtracting their first registration date in their qualification from the results date of their thesis or dissertation. Where the graduation date or HEMIS completion year is typically more available, it was presumed that the results date would avoid overestimated completion time found in previous studies. However, this divergence implies that the results from the current study may not be directly comparable to previous research in this field, or that such comparisons would be limited.

To ensure that the research remains somewhat comparable to the literature, the time to completion is described below in two formats. The first format uses the time to completion in full years (as would be considered for statutory reporting), and the second format calculates the time to completion in months (which would probably provide a more accurate estimate). The time to completion measures were further reduced by the course minimum times, where the completion times of master's and doctoral students would presumably be comparable. Records where students completed in less than the minimum time were not included in the analysis (Horta et al., 2019).

Overall, when calculating time to completion in years only, respondents who had completed their studies at a doctoral level completed within an average of 4.6 years (n = 155), with a median of four years. The minimum time for doctoral qualifications was two years (consistent with the minimum time specified in the regulations). In contrast, the maximum time respondents took to complete their doctoral qualifications was nine years. The time to completion in years for master's students indicated slightly shorter completion times. On average, master's students completed in 3.3 years (n = 423), with a median of three years. The minimum time for the completion of a master's was one year (consistent with the minimum time for such qualifications), whereas the maximum time was up to 14 years (Table 38).

To compare the time to completion between master's and doctoral qualifications, the years were transformed by reducing the time to completion for doctoral qualifications by two years and reducing the time to completion for master's by one year. This transformation estimates how much longer than the minimum time each qualification took on average to complete. The three most extreme time to completion values were altered to reduce the effects of outliers (Field et al., 2012). Three master's students took longer than eight years to complete their studies after minimum time. These estimates were replaced by 8.5 years[47] to ensure that extreme values do not skew the

[47] The weighted time to completion of 8.5 years represents just below ten-year enrolment for master's students, and just above ten years for doctoral students. Given the typical time to completion presented in section 2.3.2., this is long enough for most students, while limiting the effects of extreme cases. This approach was similar to previous research where doctoral students who took less than two years, or longer than ten years, were excluded from the analysis (Horta et al., 2019).

results further. In doctoral qualifications, students who completed took on average 2.6 years longer to finish their studies, compared to 2.3 years for those completing a master's qualification. The median time for both qualification levels indicated that it took students two years longer than the estimated minimum time. This ranged between those whose transformed time to completion was zero (who completed in the qualification minimum time), as many as seven years for doctoral candidates, and 8.5 years for master's students (Table 38).

Table 38: Time to completion in years by study level (descriptive / weighted)

	Study level	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
TTC Years	Doctoral	155	4.6	1.8	4	2	9	0.7	-0.4	0.2
	Master's	423	3.3	1.7	3	1	14	1.5	4.3	0.1
WTTC Years	Doctoral	155	2.6	1.8	2	0	7	0.7	-0.4	0.2
	Master's	423	2.3	1.7	2	0	8.5	1.1	1.5	0.1
	Total	578	2.4	1.7	2	0	8.5	1.0	0.9	0.1

* TTC (Time to completion); WTTC (Weighted time to completion)

Since registration dates and results dates provide more precise calculations for time to completion, the times for students were also calculated in months and similarly transformed after that. Although the data distributions would arguably remain very similar, this provides a more effective estimation for the completion time of students. In this study, on average, doctoral candidates took 59.4 months to complete their studies, with a median of 54 months. Master's students completed their studies in an average of 44.5 months, with a median of 39 months. Converting the average months into years indicated that doctoral candidates completed in five years, whereas master's students completed within 3.7 years. In both instances, this was around five months longer than using the statutory reporting, suggesting that using months would indicate more accurate (albeit longer) completion times for students (Table 39).

The time to completion in months for students was similarly transformed, with doctoral times being reduced by 24 months and the times for master's qualifications reduced by 12 months. Thus, the transformed times indicate how much longer than the minimum time students took to complete their studies. The same transformation was made for the three outliers, where three master's students took longer than 102 months to complete their studies, and their times were replaced by 102 months (8.5 years). Overall, doctoral candidates completed their studies on average 35.4 months after the expected time, with a median of 30 months, whereas master's students completed after 32.3 months, with a median of 27 months. The minimum time for both qualifications started at zero for those who completed within the minimum time. Across the sample of completed respondents, the doctoral candidates completed in a maximum of 88 months, and master's students completed in a maximum of 102 months after the minimum time (Table 39).

Table 39: Time to completion in months by study level (descriptive / weighted)

	Study level	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
TTC Months	Doctoral	155	59.4	21.8	54	24	112	0.6	-0.5	1.8
	Master's	423	44.5	20.3	39	12	170	1.5	4.1	1
WTTC Months	Doctoral	155	35.4	21.8	30	0	88	0.6	-0.5	1.8
	Master's	423	32.3	19.6	27	0	102	1.2	1.4	1
	Total	578	33.2	20.2	28	0	102	1	0.7	0.8

* TTC (Time to completion); WTTC (Weighted time to completion)

Further calculations in this chapter that used the time to completion of students as a measure made use of the transformed time to completion, which was calculated in months. This ensured that the times would presumably be comparable between master's and doctoral qualifications, in addition to the increased accuracy due to the more detailed calculations.

The parametric statistical assumption for normality was investigated for the transformed time to completion in months of the students. The overall skewness for the time to completion was 1, which differed slightly between doctoral candidates (0.6), and master's students (1.2). The kurtosis was 0.7 for the overall score, where again the measure was slightly closer to the zero mark for doctoral candidates (-0.5), compared to the distribution of master's students (1.4) (Table 39). Given the larger sample size, the distribution may have been considered closer to normality. However, a Shapiro-Wilk test indicated that the distribution significantly differed from a normality distribution ($W = 0.93$, $p < .001$). It should be noted that the Shapiro-Wilk test is sensitive to the sample size. Thus, a QQ-plot was created for the scores (Figure 31), seemingly indicating that the measures deviated from normality enough to imply that non-parametric statistics would be more appropriate.

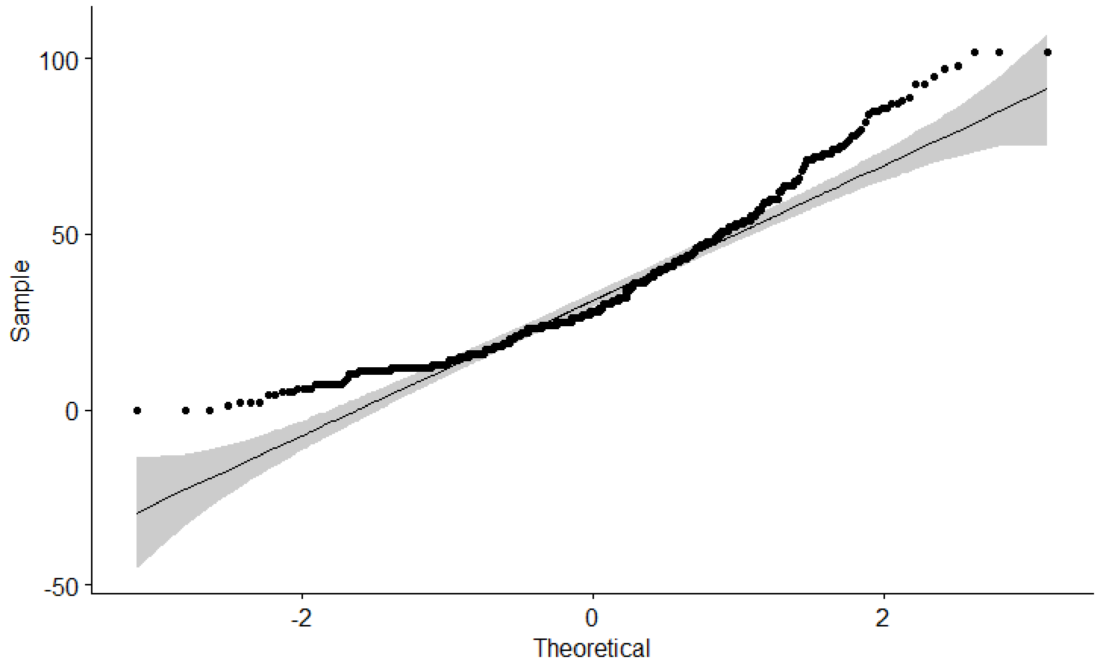


Figure 31: Student transformed time to completion in months QQ-plot

6.1.2.1. Time to completion between master's and doctoral qualifications

The weighted transformation of the master's and doctoral time to completion was intended to ensure that the different qualification levels could be compared. However, this needed to be formally tested before such an assumption could be made. Levene's test was first conducted to investigate if the variance of the time to completion between the two groups were homogeneous. Levene's test found a significant deviation from normality, which indicated that the variance was not equal ($F = 5.33$, $p = .021$). A density plot for the two scores was created since Levene's test was known to be sensitive to large sample sizes (Field et al., 2012). The density plot showed that the distributions were somewhat similar, and may be compared through nonparametric statistical measures (Figure 32).

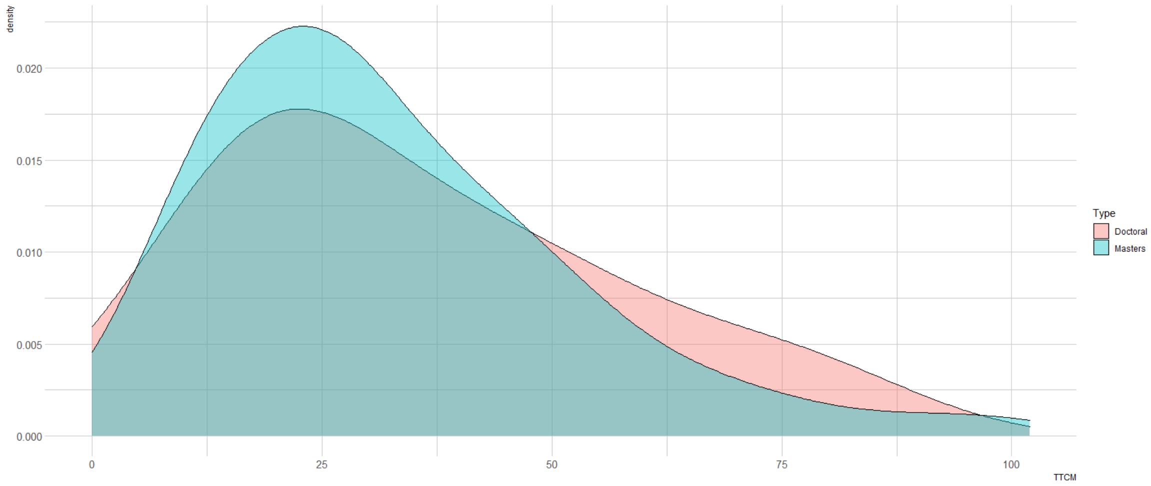


Figure 32: Student master's and doctoral time to completion density plot

A Wilcoxon rank-sum test was conducted to compare the time to completion distributions between master's and doctoral students. The test indicated that there was no significant difference between the transformed time to completion of master's students (Mdn = 27) when compared to doctoral candidates (Mdn = 30); W = 35 350, p = .149, r = 0.06. This suggests that the weighted scores make the two groups equivalent and can be combined further in the analysis.

Differentiating between qualification types (doctoral, master's by research, and master's by coursework) provided a slightly different perspective. Levene's test found a significant difference in the variance of the time to completion between the three qualification types, just below the significance threshold ($p < .05$) assumed in this study ($F = 3.45$, $p = .033$), implying that equal variance cannot be assumed. A density plot of the results, however, presented similar distributions for the three qualification groups (Figure 33). Using a Kruskal-Wallis test to compare the results, those who completed a coursework master's qualification (which involves a research component of limited scope) seemed to complete it in significantly less time (Mdn = 24) compared to those who completed a full research master's (Mdn = 30) or a doctoral degree (Mdn = 30) (Table 40). However, the effect size for the difference can be considered small, with a median of six months shorter completion time ($H(2) = 15$, $p < .001$, $\eta^2 = 0.023$).

Table 40: Student time to completion by qualification type

Qualification type	n	X̄	sd	Mdn	min	max	skew	kurt	se
Master's full research	256	34.4	19.0	30	5	102	1.0	1.1	1.2
Master's limited scope	167	29.1	20	24	0	102	1.4	2.1	1.5
Doctoral	155	35.4	21.8	30	0	88	0.6	-0.5	1.7

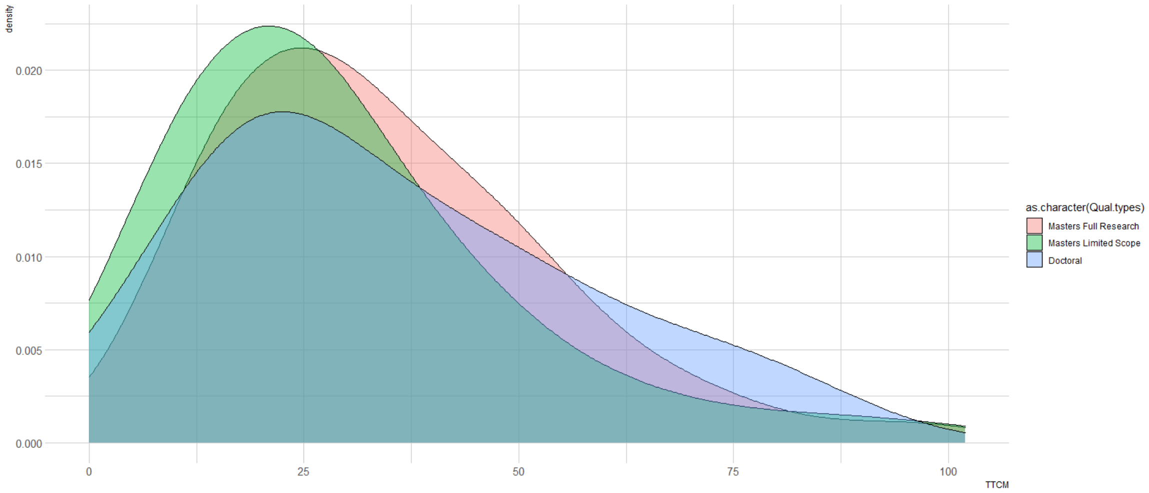


Figure 33: Student time to completion by qualification type density plot

As the median time to completion suggested, a post hoc Dunn test only found that the master's including limited-scope research to significantly differ from the other two qualification types (Table 41). Although the mean and median time to completion was shorter for those completing a master's of limited scope, the qualification type also included one of the longest completion times recorded in this project (Table 40). As such, there seemed to only be a slight gain in the time to completion for master's students who completed a project of limited scope.

Table 41: Student time to completion by qualification type post hoc Dunn's test

Comparison		z	p-value
Master's limited scope	**Master's full research**	**3.60**	**< .001***
Doctoral	**Master's limited scope**	**-3.16**	**.001***
Doctoral	Master's full research	0.06	.478

6.1.2.2. Time to completion in relation to various student characteristics

Various student characteristics were compared to explore further possible factors that may impact students' time to completion. Possible factors included students' employment status, their source of funding, within which college they studied, how their supervisors were allocated, if they changed their supervisors during their studies, and the estimated number of hours they reportedly dedicated to their studies.

Most of the respondents were **employed** either full-time (n = 453), part-time (n = 65), or were studying full-time (n = 42). As such, the time to completion was compared by employment status considering only these three categories, given the limited number of completed respondents who selected any of the other employment categories (fewer than n = 10 per category). Levene's test was not significant between the employment categories, which indicated that the variance could be considered equal (F = 0.54, p = .583). A Kruskal-Wallis test did not find a significant difference (H(2) = 1.26, p = .534, η^2 = -0.001) between the time to completion of respondents who indicated that they were employed on a full-time (Mdn = 28), or part-time (Mdn = 26) basis, nor those who were studying on a full-time basis (Mdn = 28) (Table 42).

Table 42: Student time to completion by employment status

Employment status	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Employed Full-time	453	33.1	20.1	28	0	102	1	0.8	0.9
Employed Part-time	65	30.7	20.5	26	5	97	1.4	1.5	2.5
Studying Full-time	42	32.2	17.4	28	5	71	0.6	-0.6	2.7

The **amount of time students can spend on their work** would presumably relate to their time to completion. The respondents provided the estimates on an ordinal scale, where the data was treated as separate categories. The average time to completion was calculated per category, in order to compare those who could spend more time on their studies with those not able to study as often (Table 43). Levene's test did not find a significant difference between the time to completion within the various categories, which indicated that the variance could be considered equal (F = 0.653, p = .625). A Kruskal-Wallis test did find a significant difference, although with a small effect size H(4) = 11.5, p = .021, η^2 = 0.013, between the time to completion of respondents with different reported weekly study times.

Table 43: Student time to completion by hours studied

Hours studied	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
1-9 hours	118	34.1	21.1	28.5	0	102	1.1	1.1	1.9
10-19 hours	192	36.2	20.3	32	1	102	0.8	0.3	1.5
20-29 hours	145	30.7	18.8	26	2	102	1.2	1.8	1.6
30-39 hours	60	31.6	21.5	24.5	0	88	0.8	-0.4	2.8
40 hours or more	60	29.8	19.5	22.5	4	78	0.9	-0.3	2.5

A Dunn's post hoc test (Table 44) indicated that the significant differences were primarily due to respondents who reportedly spent between 10 and 19 hours on their studies (Mdn = 32), taking between 3.5 and 9.5 months longer than the other categories. It should be noted that respondents who reported that they were only able to spend between one and nine hours per week on their studies (Mdn = 28) were just below the significance threshold (p = .049), compared to respondents who were reportedly able to spend between 40 hours or more on their studies (Mdn = 22.5). As such, it seems that respondents who spent less time on their studies per week took slightly longer to complete their qualifications compared to those who were reportedly able to devote more time, albeit with limited effect (Table 43).

Table 44: Student time to completion by hours studied post hoc Dunn's test

Comparison		z	p-value
1-9 hours	10-19 hours	-1.03	.151
1-9 hours	20-29 hours	1.32	.093
1-9 hours	30-39 hours	1.14	.128
1-9 hours	**40 hours or more**	**1.66**	**.049***
10-19 hours	**20-29 hours**	**2.59**	**.005***
10-19 hours	**30-39 hours**	**2.04**	**.021***
10-19 hours	**40 hours or more**	**2.59**	**.005***
20-29 hours	30-39 hours	0.11	.458
20-29 hours	40 hours or more	0.64	.260
30-39 hours	40 hours or more	0.45	.326

Given the importance of funding for master's and doctoral education and possible incentive to complete, students' completion times were compared by their reported **mode of funding** (Table 45). Due to small sample sizes, this analysis excluded respondents whose funding was provided by family and others. Levene's test did not find a significant difference, which indicated that the variance could be considered equal ($F = 1.17$, $p = .322$). A Kruskal-Wallis test did not find a significant difference in the time to completion between respondents who reported different primary funding methods for their studies; $H(3) = 2.41$, $p = .493$, $\eta^2 = -0.001$.

Table 45: Student time to completion by funding source

Funding	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Self	253	33.3	21.1	28	0	102	1	0.7	1.3
Employer	89	32.5	21.2	25	7	95	1	0.05	2.2
Bursary or scholarship	197	32.7	18.1	30	0	102	0.9	1.2	1.3
Multiple sources	22	39.4	22.7	37	11	89	0.5	-0.9	4.8

Respondents' time to completion across different **colleges** (Table 46), as a proxy for disciplinary differences, differed significantly. The Colleges of Accounting Science and Graduate Studies were not included in this comparison due to small sample sizes ($n = 11$ per college). Levene's test did not find a significant difference, which indicated that the variance could be considered equal ($F = 1.96$, $p = .069$). A Kruskal-Wallis test found a significant difference with a moderate effect size $H(6) = 49.9$, $p < .000$, $\eta 2 = 0.081$, between the time to completion of respondents registered in different colleges.

Table 46: Student time to completion by college

College	n	X̄	sd	Mdn	min	max	skew	kurt	se
Agriculture & Environmental Sciences	45	32.7	18.7	29	4	74	0.5	-0.8	2.8
Economic & Management Sciences	78	36.8	19.7	30	7	93	0.7	-0.3	2.2
Education	59	36.1	21.0	36	1	102	0.6	0.2	2.7
Graduate School of Business Leadership	97	23.2	16.0	23	2	88	1.9	4.1	1.6
Human Sciences	188	34.1	20.8	29	0	102	1.2	1.2	1.5
Law	32	43.3	21.8	42.5	0	87	0.4	-0.4	3.8
Science, Engineering & Technology	52	34.2	17.7	30.5	0	78	0.3	-0.6	2.5

Dunn's post hoc test (Table 47) indicated that the significant differences were driven primarily by students who completed in less time from the Graduate School of Business Leadership (M = 23.2, Mdn = 23) and students taking longer from the College of Law (M = 43.3, Mdn = 42.5). No other significant differences were found, where respondents from other colleges took, on average, between 32-36 months longer than the minimum time to complete. The median for these colleges ranged between 29 and 36 months (Table 46). Thus, although a significant difference was found, it may be questioned whether the difference represents a disciplinary distinction or a different defining characteristic between the two colleges. Nonetheless, even for the college with the shortest completion time, students, on average, took almost two years longer than the minimum time to complete their studies.

Table 47: Student time to completion by college post hoc Dunn's test

Comparison		z	p-value
Agriculture & Environmental Sciences	Economic & Management Sciences	-1.12	.132
Agriculture & Environmental Sciences	Education	-0.88	.190
Agriculture & Environmental Sciences	**Graduate School of Business Leadership**	**3.31**	**< .001***
Agriculture & Environmental Sciences	Human Sciences	-0.25	.401
Agriculture & Environmental Sciences	**Law**	**-2.29**	**.011***
Agriculture & Environmental Sciences	Science, Engineering & Technology	-0.63	.264
Economic & Management Sciences	Education	0.20	.420
Economic & Management Sciences	**Graduate School of Business Leadership**	**5.29**	**< .001***
Economic & Management Sciences	Human Sciences	1.24	.107
Economic & Management Sciences	Law	-1.53	.063
Economic & Management Sciences	Science, Engineering & Technology	0.45	.327
Education	**Graduate School of Business Leadership**	**4.66**	**< .001***
Education	Human Sciences	0.89	.187
Education	Law	-1.62	.052
Education	Science, Engineering & Technology	0.24	.406
Graduate School of Business Leadership	**Human Sciences**	**-5.10**	**< .001***
Graduate School of Business Leadership	**Law**	**-5.53**	**< .001***
Graduate School of Business Leadership	**Science, Engineering & Technology**	**-4.22**	**< .001***
Human Sciences	**Law**	**-2.56**	**.005***
Human Sciences	Science, Engineering & Technology	-0.56	.289
Law	**Science, Engineering & Technology**	**1.79**	**.037***

Respondents' time to completion did not seem to differ, due to how **supervisors were allocated or selected**. A comparison between respondents who applied through the department (n = 387), those who approached a supervisor beforehand (n = 140), and those who were allocated to a supervisor on a recommendation (n = 42) was conducted. Levene's test did not find a significant difference, which indicated that the variance could be considered equal (F = 0.47, p = .629). A Kruskal-Wallis test did not find a significant difference ($H(2) = 1.30$, $p = .521$, $\eta^2 = -0.001$) between the time to completion of respondents who reported that they were allocated a supervisor (Mdn = 28), personally approach a potential supervisor (Mdn = 30), or who were allocated a supervisor based on recommendation (Mdn = 27.5) (Table 48).

Table 48: Student time to completion by supervision allocation

Supervisor allocated	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
I applied through the department	387	33.1	20.7	28	0	102	1	0.7	1.1
I spoke to potential supervisor beforehand	140	34.4	19.3	30	4	97	1	0.6	1.6
I was recommended by someone	42	32.6	19.1	27.5	5	84	0.8	-0.1	3

To investigate the possible effect of interrupted supervision relationships, the time to completion for respondents who reportedly **changed supervisors** were compared to those who reportedly did not. Levene's test did not find a significant difference, which indicated that the variance could be considered equal ($F = 1.52$, $p = .218$). A Wilcox rank-sum test compared the time to completion between these two groups and found a significant albeit small difference in the median time to completion between those who changed supervisors (Mdn = 39.5) and those who did not (Mdn = 27) ($W = 20\ 349$, $p < .001$, $r = 0.165$). Although the effect size indicated a small difference, the median difference suggested that respondents can take about a year longer to complete their studies if they change their supervisors for whatever reason. It may be noted that the minimum time for those who changed supervisors was two months longer than those who did not change supervisors. The maximum time for both groups contained the extreme values that were artificially shortened for this analysis (102 months), suggesting that a change in supervision significantly delays completion. However, it may not necessarily delay students longer than they may have been, compared to those who do not change supervisors (Table 49).

Table 49: Student time to completion by those who did or did not change supervisors

Changed supervisor	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Yes	60	43.1	23.1	39.5	2	102	0.7	0.2	3
No	517	32	19.6	27	0	102	1	0.7	0.9

6.1.3. Student supervision style preferences

The previous chapter explored the validity and reliability of the supervision style preferences. Building on this analysis, the two-factor model indices were created by averaging the questions within the Structure and Support scales of the measurement. Classifying all scores above four on the scale as high and all scores below four as low, student preferences could be grouped according to the four-quadrant framework proposed by Gatfield (2005). Most of the student respondents were classified within the contractual style (n = 1 015, 86%). In turn, students whose preferences could be classified as directional supervision (n = 66, 6%), laissez-faire (n = 46, 4%), and pastoral supervision (n = 22, 2%) were therefore in the minority (Figure 34). Respondents who scored four for either of the constructs could not be classified in this way, given that it represents the neutral option. This affected a small number of records (n = 34, 3%).

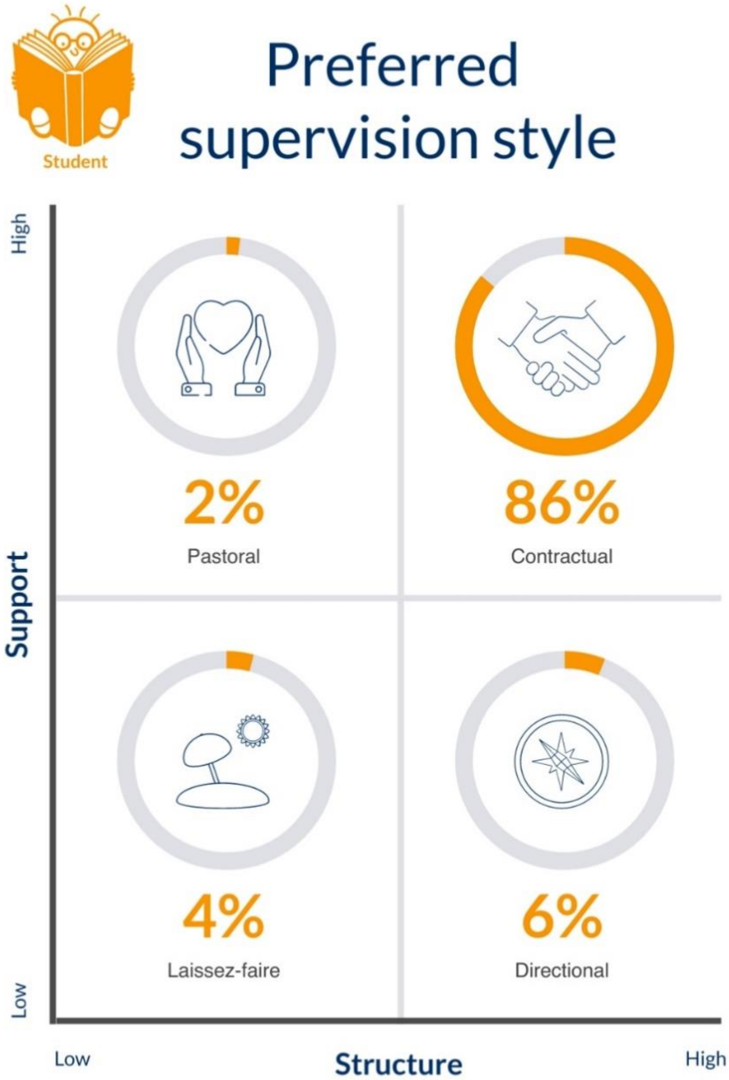


Figure 34: Preferred supervision style – student categories

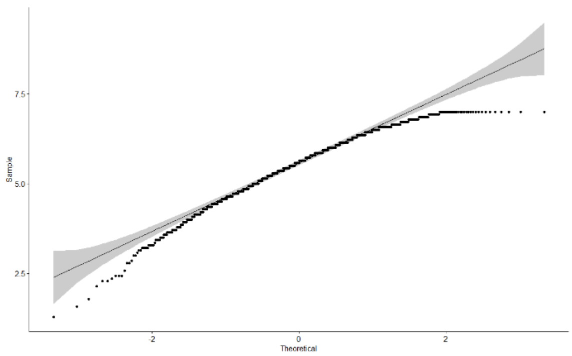
Source: Author (Visme)

The Structure and Support scales were utilised so as to investigate other possible relationships within the data that concern supervision style preferences. These scales would presumably provide clearer indications of variation within the data analysis. Overall, respondents' scores for questions related to Structure were, on average, 5.5, with a median of 5.6, and ranged between 1.3 and 7. For questions related to the Support construct, the average response was 5.3, with a median of 5.4, which ranged from 1 to 7 (the minimum and maximum extremes of the scales) (Table 50).

Table 50: Students' descriptive statistics supervision style preferences

	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	1 183	5.5	0.9	5.6	1.3	7	-0.8	0.7	0.03
Support	1 183	5.3	1.0	5.4	1	7	-0.6	0.2	0.03

One of the assumptions of parametric inferential statistics is that the measures must be normally distributed. For both measures, the skewness and kurtosis were between -1 and 1, with Structure indicating a skewness of -0.8, and kurtosis of 0.7, and the Support measure indicating a skewness of -0.6, and kurtosis of 0.2 (Table 50), which implied that the measures might have been normally distributed (according to previously presented criteria). However, a Shapiro-Wilk test indicated that for both Structure ($W = 0.963$, $p < .001$) and Support ($W = 0.97$, $p < .001$), the measures were significantly different from a normal distribution. Given that a Shapiro-Wilk test may be sensitive to large sample sizes, QQ-plots were created for each construct (Figures 35 and 36), seemingly indicating that the measures deviated from normality. Although arguably large sample sizes may be assumed to be normally distributed (Field et al., 2012), and some parametric statistics are robust against the violation of normality, the distributions were considered to deviate enough to justify a preference for non-parametric statistics.



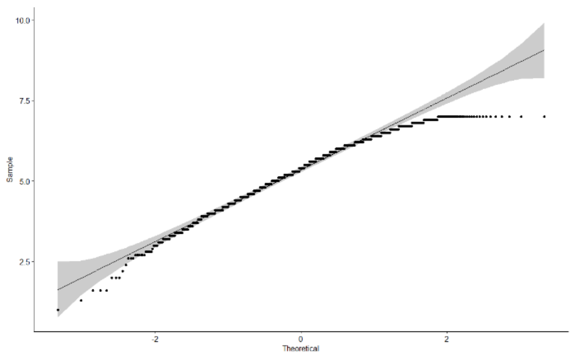


Figure 35: Student Structure QQ-Plot **Figure 36:** Student Support QQ-Plot

The results presented in the previous chapter suggest that the Structure and Support measures were related. This was formally tested again with the mean scores created based on the chosen model for the Structure and Support measures. A Spearman correlation was conducted between the two scales, where a significant positive moderate relationship was found: $r_s(1\ 181) = 0.68$, $p < .001$ (Figure 37). This may suggest that student preferences towards Structure and Support are related.

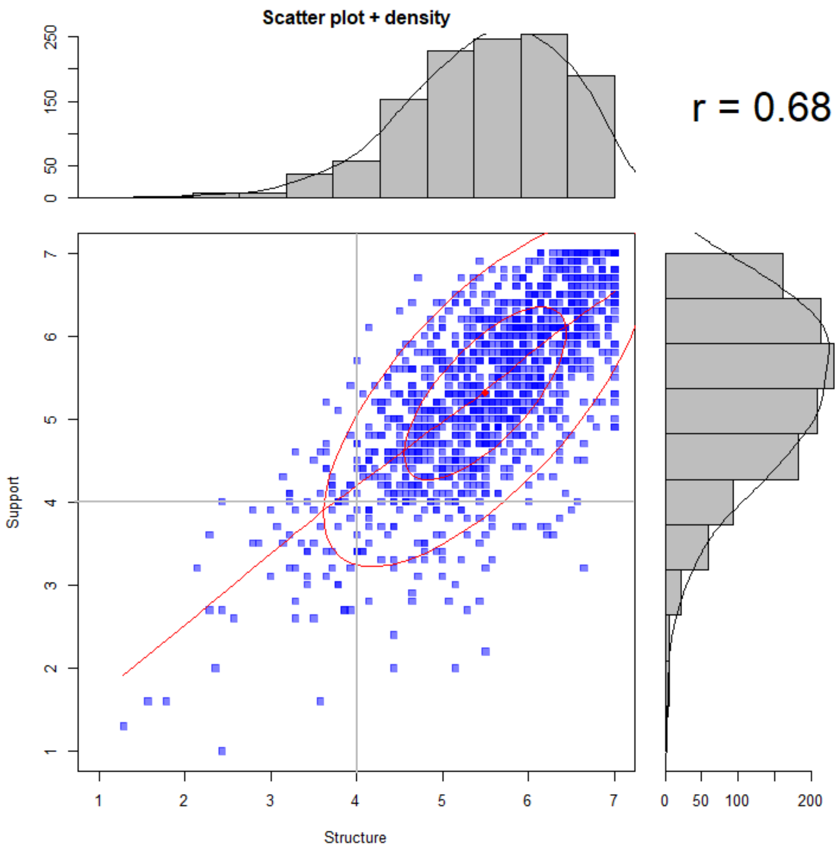


Figure 37: Student scatter plot between Structure and Support

6.1.3.1. Student supervision style preferences compared between various student characteristics

The supervision style preferences of students were further compared between various student characteristics. The comparisons focus on responding to the second research question relating to possible differences between the supervision style preferences of master's and doctoral students. "RQ 2: Is there a difference between the supervision style preferences of master's and doctoral students?" Consistent with the exploratory nature of this study, differences between other student characteristics were additionally considered (such as their completion status or the college within which they study). Within this analysis, the entire student sample was included, allowing for comparisons between those who have completed and those who have yet to complete their studies.

Across students registered for **master's or doctoral qualifications** Levene's test for both Structure ($F = 0.173$, $p = .678$) and Support ($F = 2.65$, $p = .104$) were not found to be significant. A Wilcoxon rank-sum test was conducted for both constructs and found that there was a significant difference between the scores on the Structure construct between master's (Mdn = 5.6) and doctoral (Mdn = 5.5) students (W = 149 992, p = .046, r = 0.058), albeit with a very small effect size. Similarly, there was a significant difference between the scores on the Support construct between master's (Mdn = 5.3) and doctoral (Mdn = 5.5) students (W = 176 948, p = .005, r = 0.081), also with a small effect size (Table 51).

Table 51: Students' supervision style preferences by qualification level

		n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	Doctoral	426	5.4	0.9	5.5	1.3	7	-0.7	0.6	0.05
	Master's	757	5.5	1	5.6	1.6	7	-0.8	0.8	0.03
Support	Doctoral	426	5.4	1.0	5.5	1	7	-0.8	1	0.05
	Master's	757	5.2	1.1	5.3	1.6	7	-0.5	-0.1	0.04

In response to the second research question, significant differences in the perceived supervision style needs of master's and doctoral students were found. The differences in scores appear to indicate that doctoral candidates were slightly less inclined to indicate a need for Structure and slightly more inclined to indicate a need for Support than master's students. However, significance tests are notoriously sensitive to large sample sizes, where the effect sizes for the measured differences were small. As such, it may be concluded that this difference may not be considered practically significant, and that, for all intents and purposes, master's and doctoral students shared similar preferences for specific supervision styles.

The scores for completed respondents[48] (n = 578) were disaggregated into the three **qualification types** (master's of limited scope, full research master's, and doctoral qualifications) to investigate the abovementioned difference further (Table 52). Disaggregating the analysis into the three different qualification types suggested a slightly different interpretation. Levene's test was again not significant for both the Structure scores (F = 2.50, p = .083), as well as the scores for Support (F = 0.380, p = .684). A Kruskal-Wallis test did not find any significant differences between the three

[48] Qualification types were only retained in records where students had completed their qualifications.

Structure scores ($H(2) = 0.955$, $p = .62$, $\eta^2 = -0.002$) of the different qualification types (Mdn ranging between 5.5 – 5.6), nor was there any significant differences in the post hoc Dunn test. Nonetheless, the Kruskal-Wallis test did find significant differences, albeit with a small effect, between the Support scores ($H(2) = 18.6$, $p < .001$, $\eta^2 = 0.029$) of the different qualification types.

Table 52: Students' supervision style preferences by qualification type

		n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	Master's full research	256	5.5	1	5.6	2.4	7	-0.6	-0.01	0.1
	Master's limited scope	167	5.5	0.8	5.5	2.1	7	-0.5	0.7	0.1
	Doctoral	155	5.4	0.9	5.5	2.8	7	-0.4	-0.3	0.1
Support	Master's full research	256	5.3	1	5.4	2	7	-0.4	-0.5	0.1
	Master's limited scope	167	4.9	1	5	2	6.9	-0.3	-0.5	0.1
	Doctoral	155	5.4	1	5.5	2.4	7	-0.5	-0.1	0.1

A post hoc Dunn test (Table 53) indicated that this difference was primarily between the master's of limited scope, seemingly indicating a lower need for Support (Mdn = 5.0), when compared to the median for those studying toward a full research master's (Mdn = 5.4), or doctoral qualification (Mdn = 5.5) (Table 52). Similar to the analysis above, the low effect sizes indicate that the differences are not large enough to be useful. However, the large sample size may have meant that the significance test was oversensitive. Nonetheless, respondents who completed a master's of limited scope seemed to have a slightly lower need for support compared to the full research qualification types, suggesting that this difference may not result from the qualification NQF level, but rather the nature of the course.

Table 53: Student supervision style preferences by qualification type post hoc Dunn's test (Support)

Comparison		z	p-value
Master's full research	**Master's limited scope**	**3.52**	**< .001***
Master's full research	Doctoral	-0.94	.174
Master's limited scope	**Doctoral**	**-4.00**	**< .001***

Comparing the Structure and Support scores among those who have **completed or not completed their studies** at the time provided some indication of possible differences between these two groups. For both scores, a Levene's test indicated that there were no significant differences, suggesting that the variance for the Structure (F = 0.834, p = .361) and Support (F = 0.0162, p = .899) scales were homogeneous. A Wilcoxon rank-sum test was conducted for both constructs, which found a significant difference between the scores on the Structure construct between those who have completed (Mdn = 5.5) and those who have not yet completed (Mdn = 5.6) their studies (W = 161 690, p = .025, r = 0.065), albeit with a very small effect size. Similarly, there was a significant difference between the scores on the Support construct between those who have completed (Mdn = 5.3) and those who have not yet completed (Mdn = 5.5) their studies (W = 154 805, p < .001, r = 0.099), also with a small effect size (Table 54). Both comparisons seemingly showed very low practically significant changes, albeit those who completed showed slight preferences for less Structure and Support.

Table 54: Students' supervision style preferences by completion status

		n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	Complete	578	5.5	0.9	5.5	2.1	7	-0.6	0.2	0.04
	Incomplete	605	5.5	1	5.6	1.3	7	-0.9	1.2	0.04
Support	Complete	578	5.2	1	5.3	2	7	-0.4	-0.4	0.04
	Incomplete	605	5.4	1	5.5	1	7	-0.8	1	0.04

Furthermore, the different supervision style needs of master's and doctoral students were investigated among respondents in different **colleges** as a proxy for possible disciplinary needs (Table 55). The colleges were compared for possible significant differences. Levene's test found that neither the Structure scores (F = 0.4, p = .921) nor the Support scores (F = 1.07, p = .383) indicated a significant difference, upholding the assumption of the equality of the variance between the different groups. Pertaining to the Structure scores, a Kruskal-Wallis test did not find a significant difference (H(8) = 11.5, p = .175, η^2 = 0.003). Although the post hoc Dunn test did find some significant differences, these were small, where the medians ranged between Mdn = 5.2 and Mdn = 5.7.

Table 55: Students' supervision style preferences by college

		n	X̄	sd	Mdn	min	max	skew	kurt	se
Structure	Accounting Sciences	19	5.3	0.8	5.2	3.8	7	0.1	-0.9	0.2
	Agriculture & Environmental Sciences	118	5.5	0.9	5.7	3.1	7	-0.5	-0.5	0.1
	Economic & Management Sciences	182	5.4	0.9	5.5	2.4	7	-0.4	-0.3	0.1
	Education	132	5.6	1.0	5.7	1.6	7	-1.3	3.0	0.1
	Graduate School of Business Leadership	131	5.5	0.9	5.6	2.3	7	-0.6	0.4	0.1
	Graduate Studies	34	5.5	0.9	5.4	3.2	7	-0.2	-0.5	0.2
	Human Sciences	406	5.5	1.0	5.6	2.3	7	-0.7	0.4	0.05
	Law	33	5.2	1.1	5.3	2.1	6.9	-0.6	0.1	0.2
	Science, Engineering & Technology	119	5.6	0.9	5.7	1.3	7	-1.2	3.0	0.1
Support	Accounting Sciences	19	4.8	0.8	4.8	3.0	7	0.4	1.6	0.2
	Agriculture & Environmental Sciences	118	5.7	0.9	5.8	3.2	7	-0.5	-0.6	0.1
	Economic & Management Sciences	182	5.2	1.0	5.4	2.0	7	-0.6	-0.1	0.1
	Education	132	5.4	1.1	5.6	1.6	7	-0.9	1.4	0.1
	Graduate School of Business Leadership	131	4.9	1.0	5.0	2.7	6.9	-0.2	-0.7	0.1
	Graduate Studies	34	5.2	1.2	5.7	2.0	6.8	-0.7	-0.1	0.2
	Human Sciences	406	5.3	1.1	5.3	1.0	7	-0.5	0.3	0.1
	Law	33	5.0	1.1	5.0	3.2	7	0.05	-1.1	0.2
	Science, Engineering & Technology	119	5.6	1.0	5.8	1.3	7	-1.2	2.6	0.1

In contrast, the Support scores were found to be significantly different across the various colleges ($H(8) = 53.5$, $p < .001$, $\eta^2 = 0.039$), albeit with a small effect size. The post hoc Dunn test (Table 56) showed that three groups of colleges seemed to form depending on students' preferences for supervision Support (with scores that were comparatively high, low, or in between). Although all the colleges had average scores above 4.8 and median scores above 4.8, the group that was identified to score comparatively low included Accounting Sciences (Mdn = 4.8), Graduate School of Business Leadership (Mdn = 5), and the College of Law (Mdn = 5). The group which was in the middle included the College of Graduate Studies (Mdn = 5.7), which did not significantly differ from any of the other colleges, Human Sciences (Mdn = 5.3), and Economic and Management Sciences (Mdn = 5.4), both significantly different from one or two colleges in both high and low groups. Finally, the Colleges of Agriculture and Environmental Science (Mdn = 5.8), Education (Mdn = 5.6), and Science, Engineering and Technology (Mdn = 5.8) seemed to have comparatively higher preferences for Support (Table 55). These findings suggest that most students across different colleges share a similar need for Support. Although significant differences within some colleges indicated a slightly stronger need, there was little practical significance within these differences.

Table 56: Students' supervision style preferences by college post hoc Dunn's test (Support)

Comparison		z	p-value
Accounting Sciences	**Agriculture & Environmental Sciences**	**-3.64**	**< .001***
Accounting Sciences	**Economic & Management Sciences**	**-1.95**	**.026***
Accounting Sciences	**Education**	**-2.86**	**.002***
Accounting Sciences	Graduate School of Business Leadership	-0.85	.199
Accounting Sciences	**Graduate Studies**	**-1.88**	**.030***
Accounting Sciences	**Human Sciences**	**-2.24**	**.013***
Accounting Sciences	Law	-0.76	.223
Accounting Sciences	**Science, Engineering & Technology**	**-3.40**	**< .001***
Agriculture & Environmental Sciences	**Economic & Management Sciences**	**3.63**	**< .001***
Agriculture & Environmental Sciences	Education	1.57	.059
Agriculture & Environmental Sciences	**Graduate School of Business Leadership**	**5.45**	**< .001***
Agriculture & Environmental Sciences	**Graduate Studies**	**1.85**	**.032***
Agriculture & Environmental Sciences	**Human Sciences**	**3.57**	**< .001***
Agriculture & Environmental Sciences	**Law**	**3.45**	**< .001***

Comparison		z	p-value
Agriculture & Environmental Sciences	Science, Engineering & Technology	0.46	.324
Economic & Management Sciences	**Education**	**-2.02**	**.022***
Economic & Management Sciences	**Graduate School of Business Leadership**	**2.30**	**.011***
Economic & Management Sciences	Graduate Studies	-0.37	.355
Economic & Management Sciences	Human Sciences	-0.63	.265
Economic & Management Sciences	Law	1.32	.093
Economic & Management Sciences	**Science, Engineering & Technology**	**-3.14**	**.001***
Education	**Graduate School of Business Leadership**	**4.00**	**< .001***
Education	Graduate Studies	0.84	.200
Education	**Human Sciences**	**1.74**	**.041***
Education	**Law**	**2.47**	**.007***
Education	Science, Engineering & Technology	-1.10	.136
Graduate School of Business Leadership	**Graduate Studies**	**-1.73**	**.042***
Graduate School of Business Leadership	**Human Sciences**	**-3.17**	**.001***
Graduate School of Business Leadership	Law	-0.06	.475
Graduate School of Business Leadership	**Science, Engineering & Technology**	**-5.00**	**< .001***
Graduate Studies	Human Sciences	0.07	.471
Graduate Studies	Law	1.31	.095
Graduate Studies	Science, Engineering & Technology	-1.55	.061
Human Sciences	**Law**	**1.69**	**.045***
Human Sciences	**Science, Engineering & Technology**	**-3.01**	**.001***
Law	**Science, Engineering & Technology**	**-3.15**	**.001***

Although some significant differences were found in the analysis above, effect sizes within this analysis suggested that, to some extent, students’ supervision preferences were similar across the listed variables. Slight differences across qualification types, levels of education, or colleges may suggest some development concerning the supervision needs of students, particularly relating to Support. However, given the small effect sizes, differences may be attributed to the large sample size within the analysis of the student data, rather than practical significance.

6.1.4. Students' supervision style preferences correlated with their time to completion

The second research question included a sub-question, which focused on whether the time to completion of master's and doctoral students was related to their supervision style preferences. "RQ 2.1: Is there a relationship between the supervision style preferences of master's and doctoral students and their time to completion?" To answer this question, the response scores for the Structure and Support constructs were correlated with the transformed time to completion of students. Given that the variables deviated somewhat from normality, comparisons were made with the Spearman correlation. Comparing the Structure constructs with the time to completion of students, no significant relationship was found through a Spearman correlation $r_S(576) = 0.06$, $p = .13$. A Spearman correlation was similarly conducted between the Support construct and the time to completion of students, and found a significant, albeit weak positive relationship; $r_S(576) = 0.09$, $p = .04$, which may have been related to the sample size of the current study. Students who completed shorter or longer than their peers seemingly did not indicate a clear preference for stronger or lower needs for Structure or Support. Whereas, if their supervision needs were unmet, those who took longer to complete their studies would presumably have indicated a stronger preference for a particular supervision style. As such, it may imply that students' time to completion is not driven by the supervision styles they receive. A blanket approach to supervision for master's and doctoral students may not affect their time to completion.

6.2. Supervisor RQ 3

In total, n = 180 responses to the supervision survey were used in the previous chapter to estimate the supervisors' reliability of the supervision style preference scales (see section 5.3). Of these respondents, n = 169 could be linked to the supervision information within the student sample sourced from the institutional database. Since it was possible to link this data back to the student records, the slightly reduced sample forms part of the analysis below. A descriptive overview of the supervisor respondents is provided, after which comparisons are made between various characteristics and the supervision style preferences of supervisors.

6.2.1. Supervisor sample description

Most supervisors who responded to the survey were employed internally by Unisa (n = 125, 74%) and indicated that they had a doctoral qualification (n = 130; 77%). Around a quarter of the respondents were supervised externally (n = 44; 26%) or indicated that their highest qualifications were master's degrees (n = 39; 23%). Of those who did not yet have a doctoral qualification, the majority stated that they were themselves registered for a doctorate (n = 28; 72%). Nearly all the supervisor respondents lived in South Africa (n = 164; 97%), of whom most lived within Gauteng Province (n = 149; 92%). The largest proportion of the supervisor respondents indicated that they supervised students within the College of Human Sciences (n = 50; 30%), followed by the College of Economic and Management Sciences (n = 29; 17%); and the College of Agriculture and Environmental Sciences (n = 18; 11%). The remaining colleges were represented by just under 10% of the supervisors, respectively, where the smallest two groups were the Graduate School of Business Leadership (n = 9; 5%), and the College of Graduate Studies (n = 2; 1%) (Table 57).

Table 57: Supervisor characteristics

Variable	Response	n	%
Internal / External	Employed by Unisa	125	74%
	External supervisor	44	26%
Highest Qual	Master's / MBA	39	23%
	Doctoral degree	130	77%
Studying Doctoral	Yes	28	72%
	No	11	28%
Reside SA	Yes	164	97%
	No	5	3%
SA Province	Gauteng	149	92%
	Outside Gauteng	13	8%
College	Accounting Sciences	16	9%
	Agriculture & Environmental Sciences	18	11%
	Economic & Management Sciences	29	17%
	Education	16	9%
	Graduate School of Business Leadership	9	5%
	Graduate Studies	2	1%
	Human Sciences	50	30%
	Law	14	8%
	Science, Engineering & Technology	15	9%
Total respondents		169	100%

The supervisor respondents reported that they were typically allocated students[49] as part of the departmental selection process (n = 98; 58%). Student allocation through the department was also the option selected most frequently accounting for 38% of the total responses. However, just under half also seemed to typically be approached by students (n = 77; 46%), which accounted for 30% of the responses. Comparably fewer respondents indicated that they were able to select students from a pool of applicants (n = 66; 39%), resulting in a comparably lower proportion of the total responses (26%). A few of the supervisors (n = 14; 8%) responded with the other category and stated that they are sometimes asked to co-supervise by colleagues or invited by departments, as well as that they also recruited students themselves (Table 58).

Table 58: Supervisor allocations

Supervisor allocation	n	%	Responses %
Allocated through the department	98	58%	38%
Specific students approach me	77	46%	30%
I select from a pool of applicants	66	39%	26%
Other	14	8%	5%
Total respondents	168	-	100%
Not responded	1	-	-

* Respondents could select more than one option that applied to their context. 'Responses %' may not add up to 100% due to rounding.

Based on self-report data, the supervisor respondents indicated that they supervised just over a thousand students (n = 1 126). Those supervisors who held master's qualifications were supervising or co-supervising n = 123 master's students, ranging between one student and ten per supervisor, where the median number of students was two. Supervisors who held doctoral qualifications reported supervising n = 545 master's students and n = 458 doctoral candidates. Both groups ranged between 0 and 20, with a median of three master's or doctoral students per supervisor. In total, supervisors with doctoral qualifications seemed to supervise more students when

[49] Respondents were able to select multiple responses for this question. The focus in the analysis was on which supervision allocations were used by respondents rather than the frequency of the selected options. The proportion of the overall supervision allocations are reported here to provide additional context.

compared to their peers with only master's qualifications. They supervised a median of seven students per supervisor (split between master's and doctoral students), ranging between 0 and 40 (Table 59). It can also be noted that only one supervisor respondent indicated not supervising any students, and that most of the supervisors reportedly supervised between one and ten students overall (n = 140, 83%).

Table 59: Supervisor student-load

	Holds Master's				Holds Doctorate			
Student level	n	Min	Median	Max	n	Min	Median	Max
Master's Students	123	1	2	10	545	0	3	20
Doctoral candidates	-	-	-	-	458	0	3	20
Total students	123	1	2	10	1 003	0	7	40

Most supervisor respondents estimated they had enough students (n = 79; 47%). Others indicated that they could still take on some more students (n = 65; 38%). However, some supervisors indicated they were overcommitted (n = 25; 15%). Supervisors who stated that they were overcommitted seemed to be slightly more apparent when respondents held a doctoral qualification (n = 23; 18%). However, the distribution of supervisors holding a master's may have been too small for such an interpretation (Table 60).

Table 60: Supervisor student capacity

Capacity	Holds Master's		Holds Doctorate		Total	
	n	%	n	%	n	%
I have capacity to take on some more students	18	46%	47	36%	65	38%
I have enough students	19	49%	60	46%	79	47%
I have too many students	2	5%	23	18%	25	15%
	39		130		169	

The majority of the supervisor respondents tended to agree with the statement that they can give their students enough attention, with 31% selecting strongly agree (7), and overall, 83% selecting a five or above on the seven-point scale. Similarly, most supervisor respondents indicated that they changed their supervision styles depending on the students they supervised. Overall, 28% of the respondents strongly agreed (7) with this statement, whereas 81% selected a five or above on the seven-point scale. Surprisingly, a small number of the respondents selected the strongly disagree (1) option (n = 14; 8%), suggesting that they supervise all of their students in the same way (Table 61).

Table 61: Supervisor supervision habits

		Total		Top-box scores	
Variable	Response option	n	%	n	%
Give enough attention	Strongly disagree 1	3	2%	15	9%
	2	4	2%		
	3	8	5%		
	4	13	8%	13	8%
	5	49	29%	139	83%
	6	38	23%		
	Strongly agree 7	52	31%		
Change style	Strongly disagree 1	14	8%	23	14%
	2	4	2%		
	3	5	3%		
	4	9	5%	9	5%
	5	37	22%	135	80%
	6	51	30%		
	Strongly agree 7	47	28%		

Similar to the student sample responses[50], most of the supervisor sample indicated that they used emails to communicate with their students (n = 167; 99%). Although emails accounted for a lower proportion of the total responses (25%) (Table 62) compared with the student respondents (Table 36), suggesting more varied communication methods were used by the supervisors. This was followed by one-on-one meetings (n = 136; 81%), accounting for 20% of the proportional responses, and work telephones (n = 99; 59%) accounting for 15% of the responses. Half of the sample also used private telephones to communicate with students (n = 84; 50%) along with social messaging applications (n = 81; 48%), each method accounting for

[50] Respondents were able to select multiple responses for this question. The focus in the analysis was on which communication channels were used by respondents rather than the frequency of the selected communication methods. The proportion of the overall communication methods are reported here to provide additional context.

more than 10% of the total responses. Fewer of the supervisor respondents indicated using SMSs (n = 49; 29%), or online meetings[51] (n = 38; 23%), with group meetings as the option selected by the least number of supervisor respondents (n = 17; 10%) (Table 62; Figures 38 – 40).

Table 62: Communication channels used by supervisors

Communication	n	%	Responses %
Email	167	99%	25%
Group meetings	17	10%	3%
One on one	136	81%	20%
Online meetings	38	23%	6%
Social messaging	81	48%	12%
SMS	49	29%	7%
Tel work	99	59%	15%
Tel private	84	50%	13%
Total respondents	169	-	100%

* Respondents could select more than one option that applied to their context. 'Responses %' may not add up to 100% due to rounding.

[51] The survey was distributed before the COVID-19 pandemic, and the subsequent increase in popularity of online meeting channels.

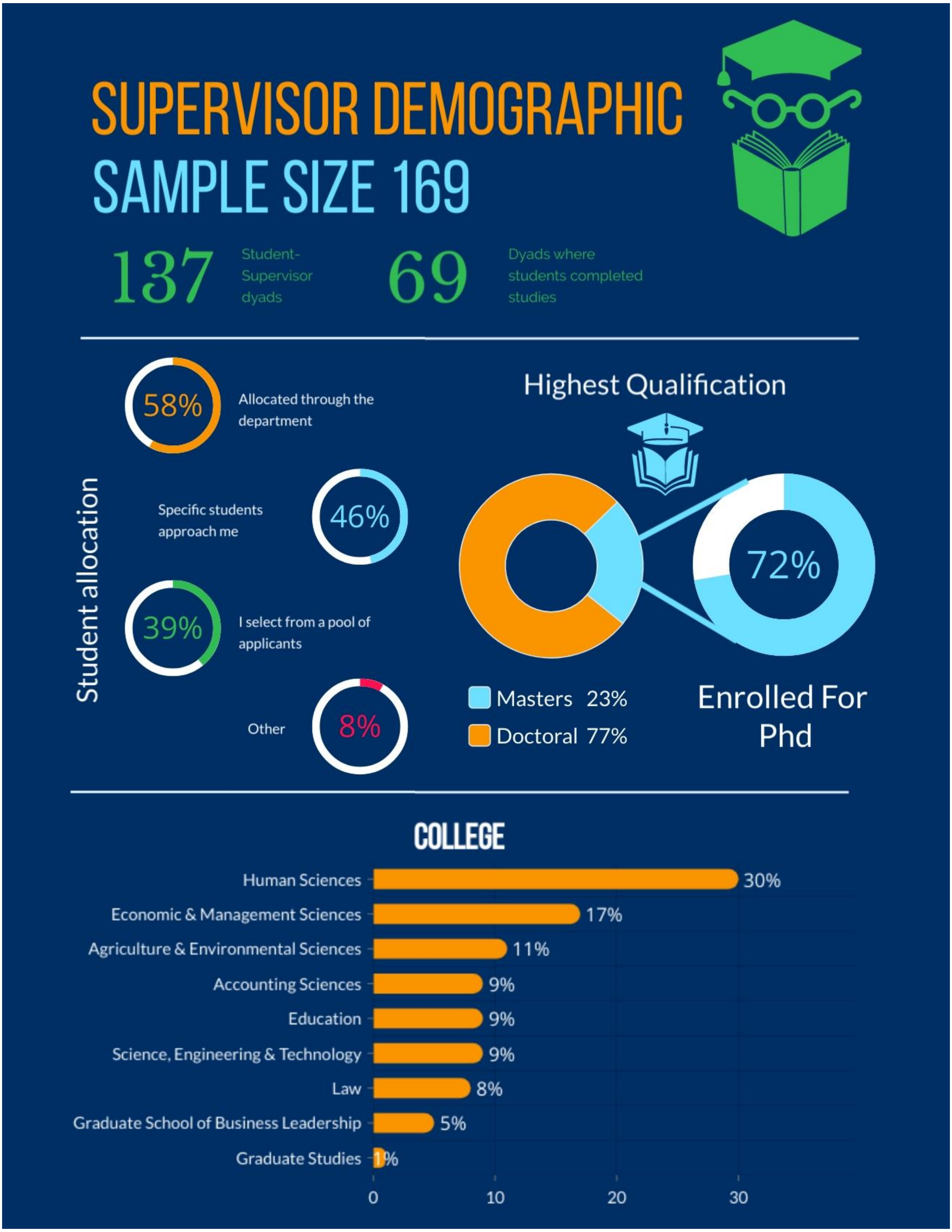


Figure 38: Descriptive statistics infographic (Supervisor) 1/3

Source: Author (Visme)

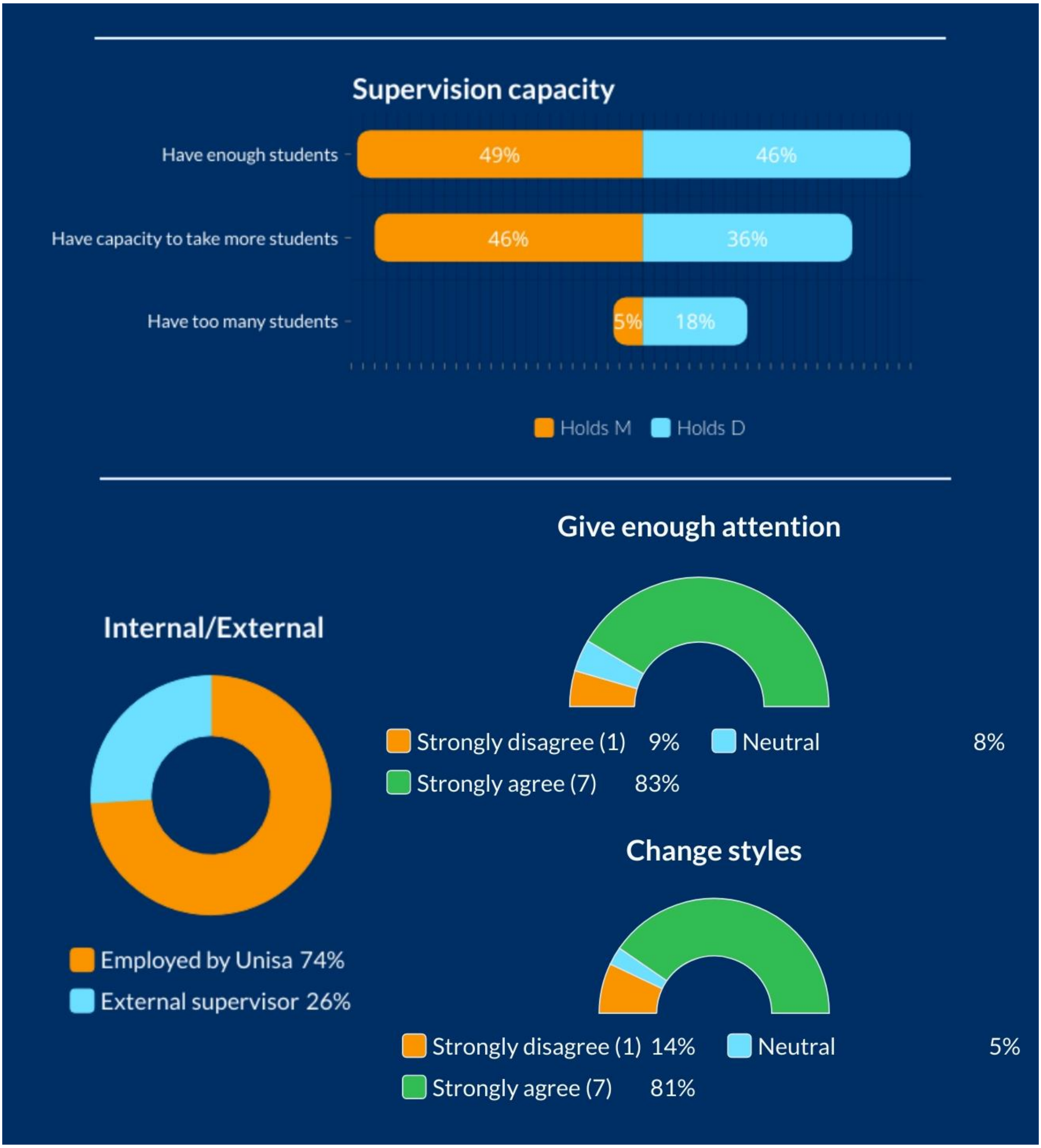


Figure 39: Descriptive statistics infographic (Supervisor) 2/3

Source: Author (Visme)

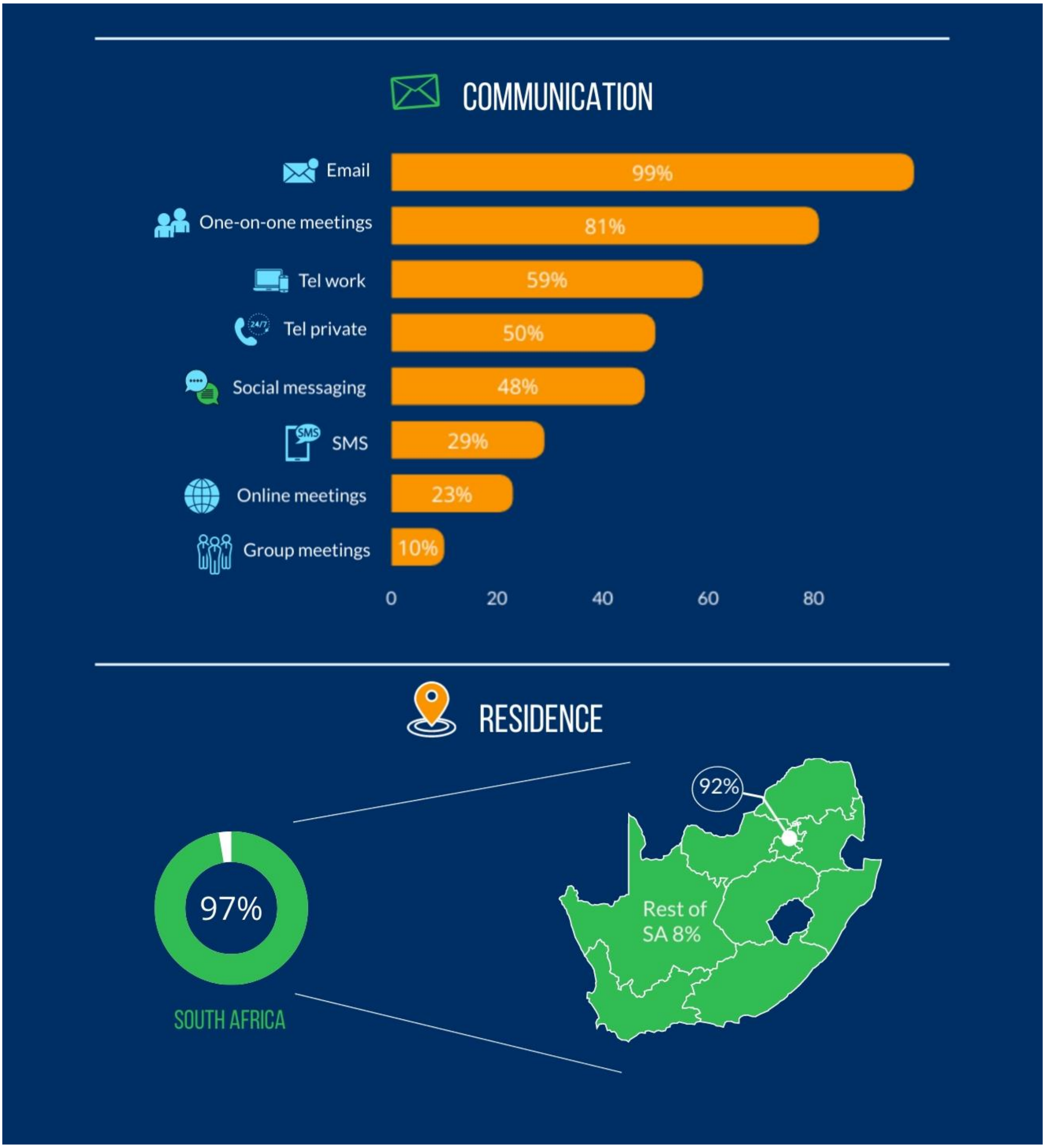


Figure 40: Descriptive statistics infographic (Supervisor) 3/3

Source: Author (Visme)

6.2.2. Supervisors' supervision style preferences

The questions relating to supervision style preferences were combined in the same way as the analysis of the student respondents (see section 6.1.3). This ensures that the scores are comparable between the student and supervisor samples. Classifying all scores above four on the scale as high and all scores below four as low, supervisors could also be grouped according to the four-quadrant framework proposed by Gatfield (2005). Most supervisor respondents were classified in this way within the contractual style (n = 124, 73%), followed by supervisors favouring directional supervision (n = 31, 18%). Those who preferred laissez-faire (n = 5, 3%), and pastoral supervision (n = 3, 2%) were thus in the minority (Figure 41). Respondents who scored four for either of the constructs could not be classified in this way, given that it represents the neutral option. This affected a small number of records (n = 6, 4%).

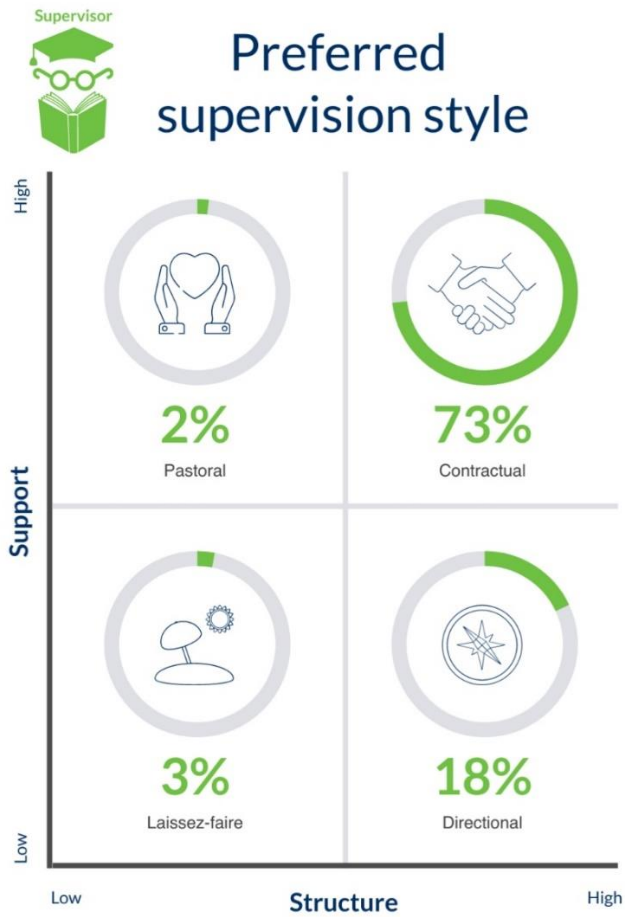


Figure 41: Preferred supervision style – supervisor categories

Source: Author (Visme)

Similar to the analysis of the student data, the Structure and Support scales were used to provide a clearer indication of variation within the analysis. Overall, respondents' scores for questions related to Structure were on average 5.3, with a median of 5.4, and ranging between 2.9 and 6.9. For questions related to the Support construct, the average response was 4.6, with a median of 4.6, which ranged from 1.7 to 7 (the minimum and maximum extremes of the scales were between one and seven) (Table 63).

Table 63: Supervisors' descriptive statistics supervision style preferences

	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	169	5.3	0.8	5.4	2.9	6.9	-0.4	-0.1	0.1
Support	169	4.6	0.9	4.6	1.7	7	0.04	0.1	0.1

One of the parametric inferential statistics assumptions is that the measures must be normally distributed. For both measures, the skewness and kurtosis were between -0.5 and 0.5, with Structure indicating a skewness of -0.4, kurtosis of 0.1, and the Support measure indicating a skewness of 0.04, and kurtosis of 0.1 (Table 63), which implied that the measures may have been normally distributed. A Shapiro-Wilk test indicated that for both Structure (W = 0.98564, p = 0.08) and Support (W = 0.9932, p = 0.618), where the measures were not significantly different from a normality distribution. QQ-plots were created for each construct (Figures 42 and 43), suggesting that the measures were distributed normally.

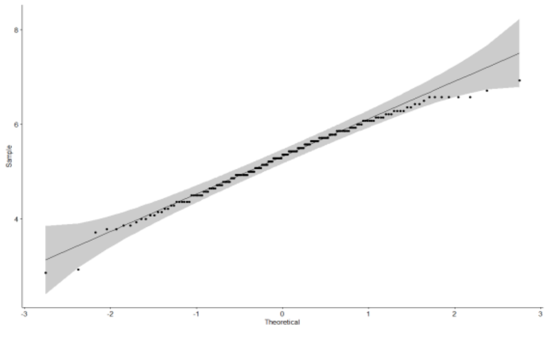


Figure 42: Supervisor Structure QQ-Plot

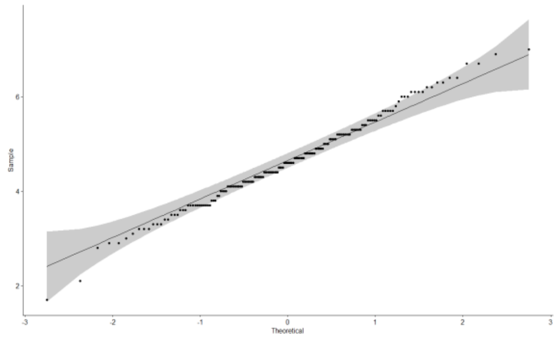


Figure 43: Supervisor Support QQ-Plot

Similar to the student data, the relationship between the Structure and Support scores was tested through a correlational analysis. This was formally tested with the mean scores created based on the chosen model for the Structure and Support measures. A Pearson correlation found a significant medium positive relationship between the two measures: $r(167) = 0.6$, $p < .001$ (Figure 44). Suggesting that supervisors who utilised more structure would similarly typically also provide more support within their preferred supervision relationships.

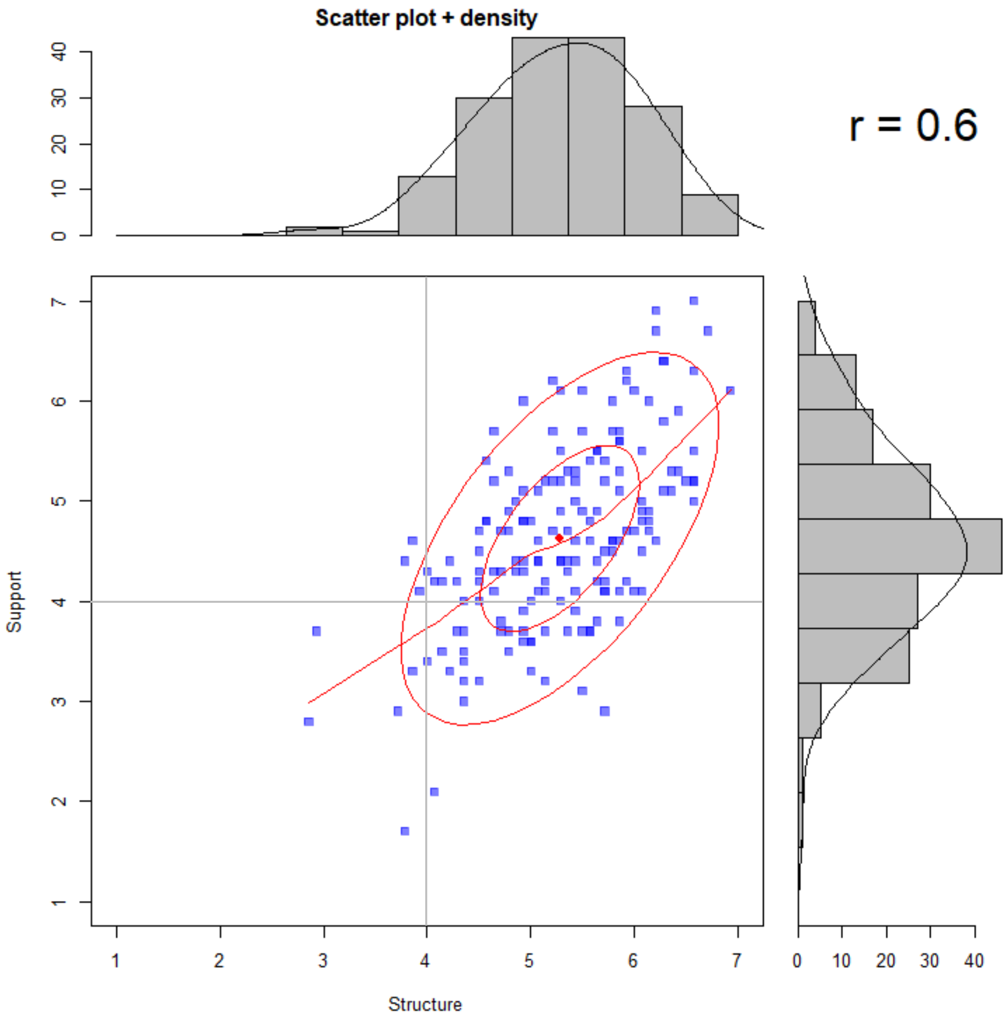


Figure 44: Supervisor scatter plot between Structure and Support

6.2.2.1. Supervisors' supervisor style preferences across various supervision characteristics

The third research question focused on factors that potentially influence the supervision style preferences of supervisors, which may be based on various characteristics related to their experience or circumstances. "RQ 3: Which factors influence the supervision style preferences of master's and doctoral supervisors?" Differences in supervision style preferences for supervisors were thus investigated as they may relate to supervisors' highest qualifications, internal or external supervision status, and the colleges through which they typically supervise. In addition, relationships were investigated where supervisors self-reported the extent to which they changed their supervision styles to the needs of their students, or the extent to which they felt they could provide each of their students with enough attention during their studies.

Supervisors' preferred Structure and Support scores were compared between those who indicated that they had a **doctoral level qualification and those who had only attained a master's** at the time of this project. Levene's test found that the variance for both the Structure ($F = 0.432$, $p = .512$) and Support ($F = 0.809$, $p = .370$) scores could be considered homogeneous, given that there were no significant differences. A Wilcoxon rank-sum test did not find a significant difference between the two samples for Structure (Mdn = 5.3 – 5.4, W = 2 664, $p = .633$, $r = 0.037$), nor their preferences towards Support (Mdn = 4.4 – 4.6, W = 2 399, $p = .613$, $r = 0.039$) (Table 64). Thus, the preferred supervision styles of supervisors did not seem to change, depending on the qualification level they attained.

Table 64: Supervisors' supervision style preferences by Highest Qualification

		n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	Hold Master's	39	5.4	0.7	5.3	4.0	6.6	-0.1	-1.0	0.1
	Hold Doctoral	130	5.3	0.8	5.4	2.9	6.9	-0.4	-0.02	0.1
Support	Hold Master's	39	4.6	1.1	4.4	2.1	7.0	0.2	-0.2	0.2
	Hold Doctoral	130	4.6	0.9	4.6	1.7	6.9	-0.04	0.1	0.1

Comparing the Structure and Support scores between **internal and external supervisors** would show whether their styles may differ due to their work contexts. Levene's test for both the Structure (F = 0.706, p = .402) and Support (F = 1.38, p = .241) scores was not significantly different, suggesting that the variance was homogeneous between the two groups. A Wilcoxon rank-sum test did not find a significant difference between the two samples for Structure (Mdn = 5.23 – 5.43, W = 2 300, p = .108, r = 0.124), nor their preferences towards Support (Mdn = 4.56 – 4.83, W = 2 400, p = .21, r = 0.097) (Table 65). It thus seems as if the supervision preferences of supervisors are not affected to a significant extent as a result of their work context.

Table 65: Supervisors' supervision style preferences of internal and external supervisors

		n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	Internal	125	5.2	0.7	5.3	2.9	6.7	-0.	-0.2	0.1
	External	44	5.4	0.9	5.4	2.9	6.9	-0.6	0.1	0.1
Support	Internal	125	4.6	0.9	4.6	1.7	6.7	-0.2	0.3	0.1
	External	44	4.8	1.0	4.8	3.3	7.0	0.4	-0.8	0.2

As a proxy for disciplinary differences, supervisors' preferences for Structure and Support were compared across different **colleges** within the institution (Table 66). Within this analysis, the Graduate School of Business Leadership (n = 9) and the College of Graduate Studies (n = 2) were excluded, given the small sample sizes of each group. Levene's test for both the Structure (F = 0.546, p = .773) and Support (F = 0.913, p = .488) scores did not show a significant difference, suggesting that the variance was homogeneous between the groups.

Table 66: Supervisors' supervision style preferences by college

		n	X̄	sd	Mdn	min	max	skew	kurt	se
Structure	Accounting Sciences	16	5.2	0.6	5.1	4.3	6.4	0.2	-1.0	0.1
	Agriculture & Environmental Sciences	18	5.8	0.8	6.1	3.9	6.7	-1.0	0.03	0.2
	Economic & Management Sciences	29	5.2	0.8	5.4	2.9	6.1	-1.1	0.5	0.1
	Education	16	5.4	0.7	5.6	4.0	6.4	-0.5	-0.9	0.2
	Human Sciences	50	5.1	0.7	5.0	2.9	6.1	-0.6	0.6	0.1
	Law	14	5.1	0.8	5.1	3.9	6.6	0.2	-1.2	0.2
	Science, Engineering & Technology	15	5.5	0.9	5.4	4.1	6.9	0.1	-1.4	0.2
Support	Accounting Sciences	16	4.5	0.7	4.5	3.2	5.6	-0.3	-0.9	0.2
	Agriculture & Environmental Sciences	18	5.5	0.9	5.4	4.1	7.0	0.2	-1.3	0.2
	Economic & Management Sciences	29	4.5	1.0	4.4	1.7	6.1	-0.5	0.1	0.2
	Education	16	4.5	0.7	4.4	3.5	6.0	0.5	-0.8	0.2
	Human Sciences	50	4.6	0.8	4.6	2.8	6.2	-0.04	-0.3	0.1
	Law	14	3.7	0.7	3.7	2.1	5.0	-0.2	-0.4	0.2
	Science, Engineering & Technology	15	5.2	0.7	5.1	4.1	6.3	-0.1	-1.5	0.2

Investigating differences in terms of supervisors' preference towards Structure scores ($H(6) = 18.7$, $p = .005$, $\eta^2 = 0.084$), a significant medium difference was found. A post hoc Dunn test (Table 67) indicated that the preferences of supervisors in the College of Agriculture and Environmental Sciences (Mdn = 6.1) were significantly higher than the preferences of supervisors in almost all the other colleges, except for Education (Mdn = 5.6) and Science, Engineering and Technology (Mdn = 5.4). In addition, the preferences of supervisors in the College of Science, Engineering and Technology (Mdn = 5.4) were significantly higher compared to supervisors' preferences in the College of Human Sciences (Mdn = 5.0) (Table 66).

Table 67: Supervisors' supervision style preferences by college post hoc Dunn's test (Structure)

Comparison		Z	p-value
Accounting Sciences	**Agriculture & Environmental Sciences**	**-2.50**	**.006***
Accounting Sciences	Economic & Management Sciences	-0.04	.483
Accounting Sciences	Education	-0.93	.176
Accounting Sciences	Human Sciences	0.74	.230
Accounting Sciences	Law	0.55	.292
Accounting Sciences	Science, Engineering & Technology	-1.02	.154
Agriculture & Environmental Sciences	**Economic & Management Sciences**	**2.81**	**.002***
Agriculture & Environmental Sciences	Education	1.54	.062
Agriculture & Environmental Sciences	**Human Sciences**	**3.89**	**< .001***
Agriculture & Environmental Sciences	**Law**	**2.97**	**.002***
Agriculture & Environmental Sciences	Science, Engineering & Technology	1.40	.080
Economic & Management Sciences	Education	-1.02	.155
Economic & Management Sciences	Human Sciences	0.97	.167
Economic & Management Sciences	Law	0.66	.255
Economic & Management Sciences	Science, Engineering & Technology	-1.11	.133
Education	**Human Sciences**	**1.89**	**.030***
Education	Law	1.45	.074
Education	Science, Engineering & Technology	-0.10	.458
Human Sciences	Law	-0.04	.485
Human Sciences	**Science, Engineering & Technology**	**-1.97**	**.025***
Law	Science, Engineering & Technology	-1.53	.063

In addition, a significant large difference was found in terms of the measure for Support ($H(6) = 34.8$, $p < .001$, $\eta^2 = 0.191$). A post hoc Dunn test (Table 68) showed that the Support scores for the colleges of Agriculture and Environmental Sciences (Mdn = 5.4), and Science, Engineering and Technology (Mdn = 5.1), were significantly higher than all the other colleges within the sample. At the same time, the College of Law's Support score (Mdn = 3.7) was significantly lower than that of all the other colleges (Table 66). Although significant differences typically only involved colleges with particularly high or low scores, some differences in supervision preference seemed apparent within this study. Colleges nonetheless shared similarities in their approaches to supervision, given that most of the scores seemed to suggest a tendency towards slightly higher Structure and Support.

Table 68: Supervisors' supervision style preferences by college post hoc Dunn's test (Support)

Comparison		z	p-value
Accounting Sciences	**Agriculture & Environmental Sciences**	**-3.05**	**.001***
Accounting Sciences	Economic & Management Sciences	-0.16	.436
Accounting Sciences	Education	-0.18	.429
Accounting Sciences	Human Sciences	-0.43	.335
Accounting Sciences	**Law**	**2.21**	**.014***
Accounting Sciences	**Science, Engineering & Technology**	**-2.30**	**.011***
Agriculture & Environmental Sciences	**Economic & Management Sciences**	**3.32**	**< .001***
Agriculture & Environmental Sciences	**Education**	**2.86**	**.002***
Agriculture & Environmental Sciences	**Human Sciences**	**3.36**	**< .001***
Agriculture & Environmental Sciences	**Law**	**5.20**	**< .001***
Agriculture & Environmental Sciences	Science, Engineering & Technology	0.63	.264
Economic & Management Sciences	Education	-0.04	.483
Economic & Management Sciences	Human Sciences	-0.31	.378
Economic & Management Sciences	**Law**	**2.63**	**.004***
Economic & Management Sciences	**Science, Engineering & Technology**	**-2.44**	**.007***
Education	Human Sciences	-0.21	.419
Education	**Law**	**2.38**	**.009***
Education	**Science, Engineering & Technology**	**-2.12**	**.017***
Human Sciences	**Law**	**3.07**	**.001***
Human Sciences	**Science, Engineering & Technology**	**-2.39**	**.009***
Law	**Science, Engineering & Technology**	**-4.39**	**< .001***

The supervision style preferences of supervisors seemed to be influenced by their **willingness to adapt their styles** to suit their students. A significant albeit small positive relationship was found between the two variables in the study. A Spearman correlation was tested for significant associations, given the scale's ordinal nature and question. Respondents who reported stronger agreement with the statement that they change their styles dependent on who they supervise tended to prefer relationships with higher Structure ($r_s(165) = .26$, $p < .000$) as well as higher Support ($r_s(165) = .26$, $p < .000$). Suggesting that those supervisors who were more involved with their students may have also been more willing to change their styles of interaction if needed.

In addition, supervisors who felt they could **give enough attention** to each of their students were also more likely to score higher for both Structure and Support. A Spearman correlation was tested for significant associations given the scale's ordinal nature and question. Respondents who reported stronger agreement to the statement that they were able to give enough attention to each of their students, also tended to prefer relationships with higher Structure ($r_s(165) = .38$, $p < .001$) and higher Support ($r_s(165) = .37$, $p < .001$). This comparison may relate somewhat to the nature of the Structure and Support constructs, given that lower scores suggest a more distant or hands-off approaches to supervision. Those with higher Structure and Support scores may feel they spend enough time with each student because their contact points may be more frequent. In contrast, those who prefer a more distant approach may depend on their students' initiative to arrange supervision meetings, which may be less frequent.

6.3. Supervision relationship RQ 4

Within this study, a total of n = 137 student-supervisor dyads could be linked, where both students and their supervisors completed the online survey. Of these dyads, a total of n = 69 students had completed their studies at the time that the data was requested. The measure of supervision fit (the difference between the Structure and Support scores of students and their supervisors) was created and explored for the full n = 137 sample. However, only the completed responses could be used to measure the relationship between supervision fit and students' time to completion in answer to the final research question. “RQ 4: Is there a relationship between the congruence of supervision relationships and the time to completion of master’s and doctoral students?”

As previously described, relationship scores for the Structure and Support constructs were created by subtracting the students’ scores from their supervisors’ scores. Since the relationship scores differ between students’ and their supervisors’ scores, these theoretically range from -7 to 7. Thus, a positive score indicates that supervisors provide more of the construct than their students require. In contrast, a negative score indicates that students’ preferences are not met by their supervisors. A score closer to zero (the mid-point of the created indices) would thus be considered more congruent since students and supervisors would have had similar scores (Figure 45).

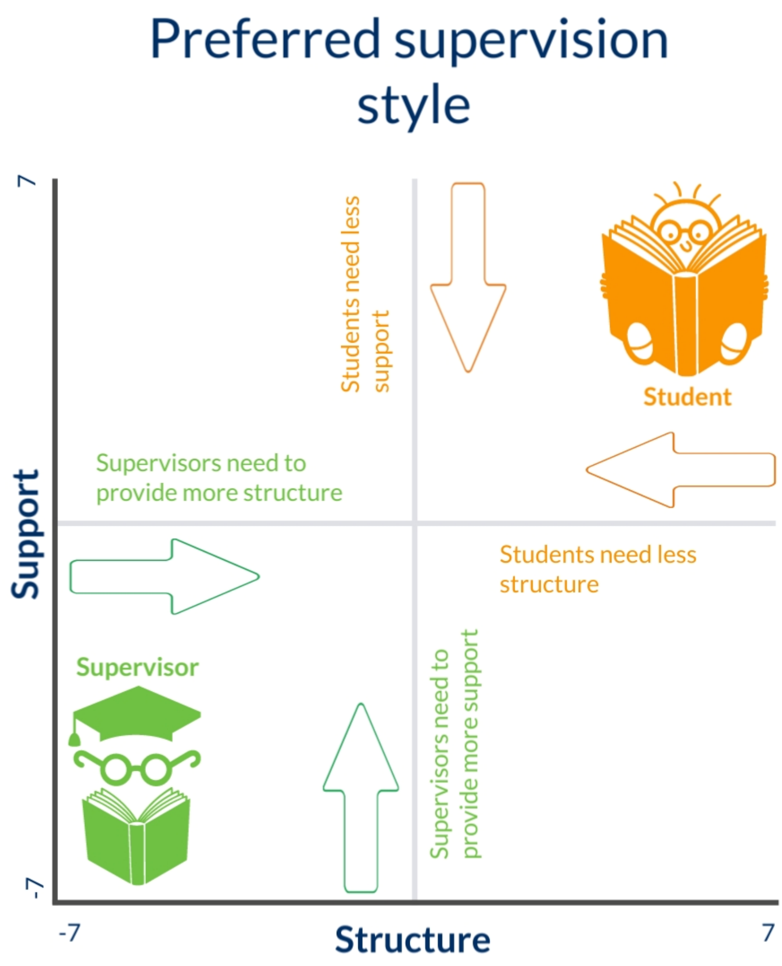


Figure 45: Preferred supervision style – relationship

Source: Author (Visme)

The mean difference between the supervision style preferences of supervisors and their students was just below zero. Differences in the Structure construct were, on average, M = -0.03, with a Mdn = -0.1. The Structure scores ranged between -2.4 and 3.9. The differences in the Support construct were, on average, M = -0.7, with an Mdn = -0.8, and ranged between -2.8 and 2.5 (Table 69).

Table 69: Descriptive statistics supervision relationship fit

	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure	137	-0.03	1.2	-0.1	-2.4	3.9	0.4	0.2	0.1
Support	137	-0.7	1.1	-0.8	-2.8	2.5	0.4	-0.3	0.1

Both the combined Structure and Support constructs seemed to have been normally distributed. The kurtosis and skewness scores for both constructs were between -0.5 and 0.5 (Table 69). A Shapiro-Wilk test did not find a significant difference between the combined Structure construct and that of a normality distribution (W = 0.98267, p = .08). However, the same statistic suggested that there was a significant difference for the Support construct (W = 0.9801, p = .043), just below the required threshold. The QQ-plots for both measures (Figures 46 and 47) suggested that the distributions were normal, although non-parametric statistics were nonetheless used due to the small sample size.

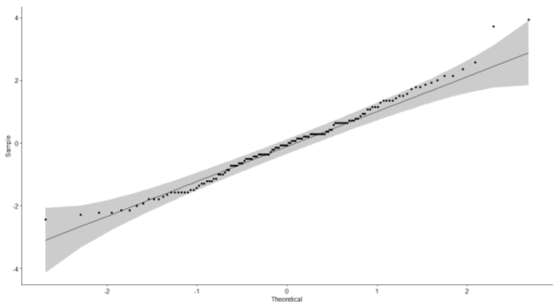


Figure 46: Supervision relationship fit Structure QQ-Plot

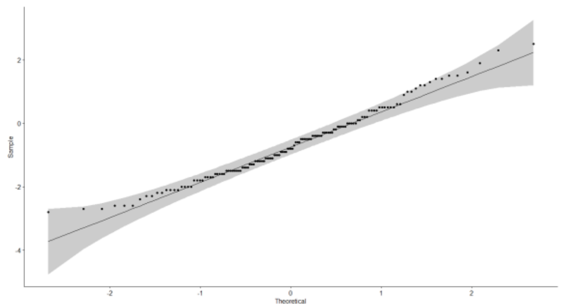


Figure 47: Supervision relationship fit Support QQ-Plot

The supervision fit for the Structure and Support construct was compared between students who had completed and those who had not completed their studies. The Levene's test conducted between the two samples did not find a significant difference in either the Structure ($F = 0.122$, $p = .727$) or the Support ($F = 1.33$, $p = .250$) constructs, suggesting that the variance was equal in both instances. A Wilcoxon rank-sum test did not find a significant difference between the two samples for Structure ($Mdn = -0.1 - 0.0$, $W = 2\ 410$, $p = .783$, $r = 0.024$), nor Support ($Mdn = -0.8 - -0.8$, $W = 2\ 414$, $p = .77$, $r = 0.025$), suggesting that both groups could be said to have been equivalent.

A similar relationship between the Structure and Support constructs was evident within the combined scores, as presented previously in the analysis of the findings for students and supervisors. The combined relationship fit constructs for Structure and Support were significantly positively correlated with a Spearman correlation test; $r_s(135) = 0.66$, $p < .001$ (Figure 48). As such, relationships where students' preferred styles differed from that of their supervisors, seemed to be related to both in terms of Structure as well as Support.

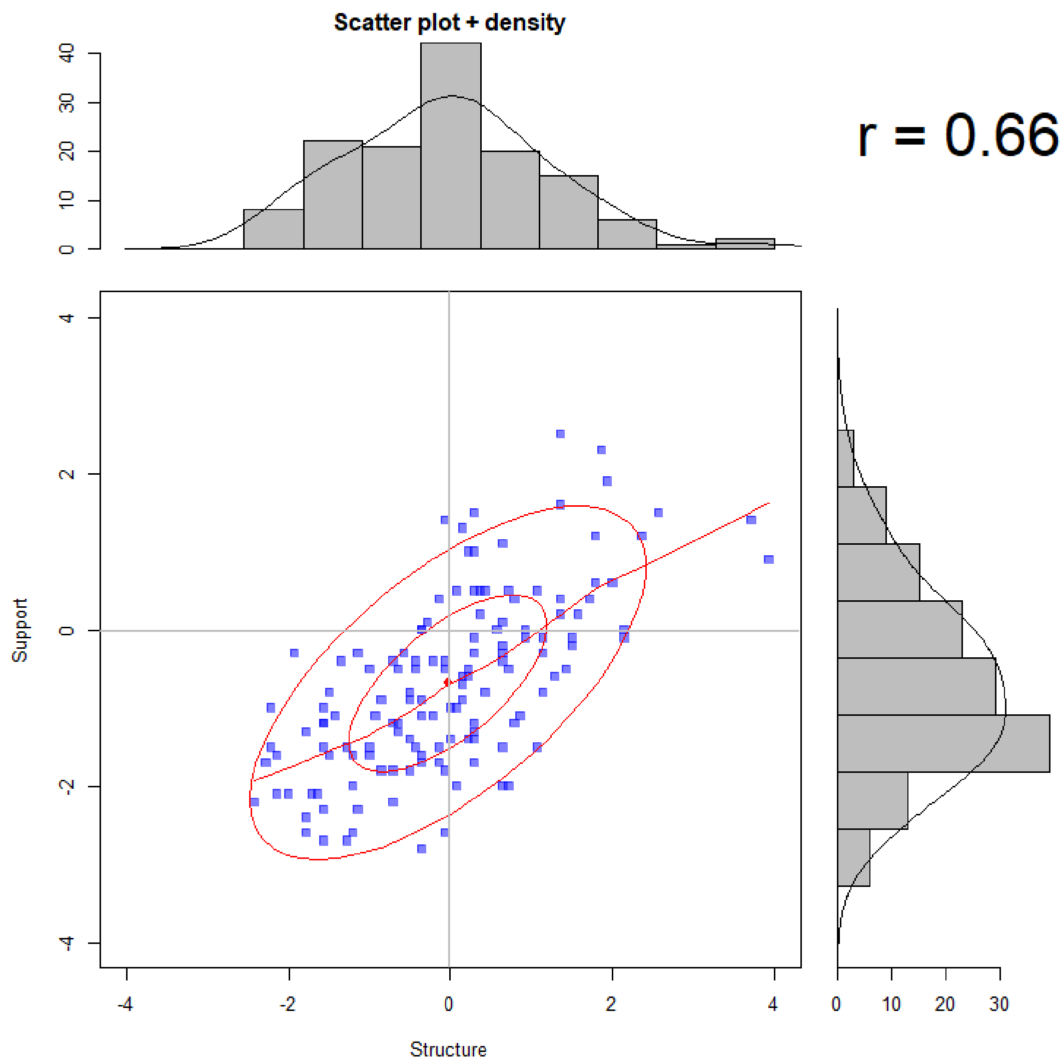


Figure 48: Supervision relationship fit scatter plot between Structure and Support

6.3.1. Time to completion compared with supervision fit and other variables

The final research question aimed to investigate the possible relationship between students' time to completion, and their supervision fit, measured through the supervision style preferences of the students and their supervisors. To investigate this possible relationship, a spearman correlation was conducted between the transformed time to completion in months previously described and each of the two supervision fit variables for Structure and Support for students who had completed their studies. The Spearman correlation did not find significant relationships between the two variables, with particularly low correlation values in both constructs, i.e., Structure $r_s(67) = 0.09$, $p = .46$; Support $r_s(67) = 0.05$, $p = .69$. Thus, although supervisors seemed to on average fall short of their students' expectations, this did not seem to be related to how quickly students were able to complete their studies.

A narrower definition of congruence may be required to answer the final research question fully. Within the analysis above congruence within supervision relationships are reflected closer to the scale mid-point, where more incongruent relationships (either positive or negative scores) may not be presented as a linear relationship. To further explore this reasoning, the Structure and Support constructs for the supervision relationships were transformed to absolute values, where larger deviations from zero would be considered more incongruent (regardless of the direction of this incongruence). The transformed absolute value for the Structure construct had a mean of 1 and a median of 0.7, whereas the Support construct had a mean and median of 1.1 (Table 70).

Table 70: Descriptive statistics supervision relationship fit (Absolute values)

	n	$\bar{X}$	sd	Mdn	min	max	skew	kurt	se
Structure (Abs)	137	1.0	0.8	0.7	0	3.9	1.0	1.3	0.1
Support (Abs)	137	1.1	0.7	1.1	0	2.8	0.4	-0.8	0.1

The absolute values of the combined Structure and Support constructs seemed to deviate slightly from normality. The kurtosis (1.3) and skewness (1.0) scores for the Structure construct were slightly over one, although for the Support construct, the kurtosis (-0.8) and skewness (0.4) were lower. A Shapiro-Wilk test found significant differences between the absolute score of the combined Structure construct and that of a normality distribution ($W = 0.909$, $p < .001$), as well as for the absolute score of the Support construct ($W = 0.955$, $p < .001$), which can be interpreted as a slight deviation from normality.

A Spearman correlation was conducted to test whether there was a significant relationship between the absolute values for the Structure and Support scores and the students' completion time. Within this study no significant relationships were found between either absolute value for supervision fit of Structure ($r_s(67) = -0.05$, $p = .67$) nor Support ($r_s(67) = -0.08$, $p = .53$) and the time to completion for master's and doctoral students. The low correlation scores can be interpreted to suggest that the congruence of the supervision relationships does not relate strongly enough to the time to completion of master's and doctoral students.

6.4. Chapter summary

In this chapter, the results were presented on the relationship between student-supervisor fit and time to completion of students in master's and doctoral education. Towards this end, the results were primarily directed at answering the remaining three research questions. Facilitating this process, the chapter was divided into three sections: 1) student data focusing on the findings from the student survey; 2) supervisor data focusing on the findings from the supervision survey; 3) finally the supervision relationship data, which consisted of a combination of data from the two samples.

The student data presented findings which responded to the second research question and sub-question. The results indicated that the difference between the supervision style preferences of master's and doctoral students was not practically significant and the statistically significant finding likely resulted from the large sample size within the analysis (RQ 2). However, a further disaggregation seemed to suggest that students studying a master's of limited scope may require slightly less Support from their supervisors compared to those studying a full-research master's or doctoral qualification. Nonetheless, master's and doctoral students may be considered similar when it comes to their supervision style preferences overall. In addition, students who completed in a shorter or longer time than their peers seemingly did not indicate a clear preference for stronger or lower needs for Structure or Support (RQ 2.1).

The results of the supervisor survey assisted in addressing the third research question, identifying possible factors that may influence the supervision style preferences of master's and doctoral supervisors (RQ 3). Data on master's and doctoral supervisors primarily relied on self-report responses obtained in the survey. From these findings, it seemed that supervisors' supervision style preferences did not depend on their level of education (having a master's or doctoral degree) nor on their work context (employed internally or externally). This may suggest that supervision style preferences may already be entrenched after supervisors have completed their master's qualifications, and that such preferences may not be entirely institutionally dependent. There were, however, some significant differences between different colleges, suggesting that there may be some differences in preferences due to disciplinary context. However, such differences were seemingly only found in the case of colleges with particularly high or low Structure or Support scores. Different colleges nonetheless shared similarities in their approaches to supervision, given that most of the scores seemed to suggest a tendency towards slightly higher Structure and Support. Furthermore, supervisors who reportedly changed their supervision style depending on their students and those who felt they could give each of their students enough attention seemed to be positively related to Structure and Support scores. Although the relationships were weak, it is noteworthy to consider that supervision style preferences are likely influenced by multiple factors and may be related more strongly to personal constructs rather than organisational factors.

Finally, the supervision fit between students and their supervisors was compared to answer the last research question. Within this study, the congruence between student and supervisor fit pertaining to supervision style preferences was not significantly related to students' completion time (RQ 4). Although the sample size for this section of the study was small, the weak correlation and non-significant findings suggest that the supervision fit might not be related to shorter completion times for master's and doctoral education within an ODeL context.

This finding does not suggest that supervision relationships are unimportant in master's and doctoral studies. However, the findings do question initiatives aimed at supervisory fit that intend to improve the completion times of master's and doctoral students. The time to completion at this study level may thus be more strongly related to students' personal characteristics, which would need to be investigated in further research. In addition, investigating the impact of supervision relationship on the throughput or dropout of master's and doctoral students may become important for the larger research focus on postgraduate education.

The following chapter provides a discussion of the findings presented here. The concluding chapter of this project will aim to contextualise the presented results into the broader literature review discussed in previous chapters. In addition to discussing possible recommendations and limitations of the project, which may need further consideration.

Chapter 7: Discussion and conclusion

Research relating to master's and doctoral student education has received considerable attention in the literature (ASSAf, 2010; Fourie, 2016; Hasgall et al., 2019; Jones, 2013; Manyike, 2017; Mouton et al., 2015; Sverdlik et al., 2018; Van Lill, 2019). With a particular focus on improving the efficiency (time to completion) of master's and doctoral training to increase participation in the knowledge economy (Cloete et al., 2015; Deuchar, 2008; Laher et al., 2019; Mouton, 2011). Within the literature, supervision has been identified as crucial to student progress and could influence their time to completion (Dominguez-Whitehead & Maringe, 2020; Jones, 2013; Murphy, 2009; Van de Schoot et al., 2013; Van Lill, 2019). However, there has been a dearth of empirical studies investigating student supervision (Ali et al., 2016; Vilkinas, 2008) and its impact on the time to completion of master's and doctoral students.

To address this gap in research, this study aimed to collect empirical data through the measurement of supervision style preferences of master's and doctoral students and their supervisors. The measurement was based on the theoretical conceptualisation of supervision proposed by Gatfield (2005). A correlational cross-sectional research design formed the basis for the research, where data were collected through online survey instruments. These measurements were used to determine the supervision-relationship fit between students and their supervisors and to investigate its impact on the completion time of master's and doctoral students.

The final chapter revisits the purpose of the study and contextualises the results within the literature previously presented in Chapter Two. The discussion of the results is organised in a similar pattern as in the previous chapters and will be presented in the order of the research questions. This is followed by the limitations of the research before concluding with a brief overview of key discussion points and recommendations for future studies.

7.1. Research questions

As discussed in the study background (see section 1.1), higher education institutions have increasingly become concerned with improving the efficiency of higher education qualifications, specifically at master's or doctoral levels. Students have been found to take substantially longer than the qualification's minimum time to complete their studies. On average, Unisa master's students completed in 3.7 years, and doctoral candidates completed their studies in just under five years (see section 6.1.2). In the literature, master's students complete on average between two and three years (Council on Higher Education, 2009a; Zewotir et al., 2015), and doctoral candidates, on average complete in just under five years (ASSAf, 2010; Council on Higher Education, 2009a; Mouton, 2007; Van Lill, 2019). As such, previous studies have investigated what factors possibly influence students' time to completion (Van Lill, 2019).

The purpose of this study was thus to investigate whether student-supervisor relationships affected the time to completion of master's and doctoral students. Four research questions were formulated:

- RQ 1: Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?
- RQ 2: Is there a difference between the supervision style preferences of master's and doctoral students?
    - RQ 2.1: Is there a relationship between the supervision style preferences of master's and doctoral students and their time to completion?
- RQ 3: Which factors influence the supervision style preferences of master's and doctoral supervisors?
- RQ 4: Is there a relationship between the congruence of supervision relationships and the time to completion of master's and doctoral students?

The results of this study were discussed in sections that responded to each of the research questions. Chapter Five, concerned with the research instrument's validity and reliability, addressed the first research question (see section 5.3). Chapter Six provided the evidence for the remaining research questions. The results chapter was divided into sections, which each addressed aspects of the analysis relating specifically to the student data (section 6.1), the supervisor data (section 6.2), and the relationships between students and supervisors (section 6.3). The discussion for the remaining part of the chapter will similarly be divided, starting with the contextualisation of the measurement validity and reliability.

7.2. Validity and reliability of the research instrument (RQ 1)

Is the developed research instrument a valid and reliable measurement of supervision styles as proposed by Gatfield?

A questionnaire of supervision style preferences was designed for this study due to the lack of available robust measurements aimed at student supervision (Ali et al., 2016; Vilkinas, 2008). Although some instruments were found in the literature, these were determined to fall outside the scope of the current research (Table 13). The created questionnaire was developed to measure preferences of supervision relationships based on the conceptualisation of supervision styles by Gatfield (2005).

The research instrument initially included 51 Likert-type items, where 31 items were operationalised to measure Gatfield's (2005) Structure construct and 20 items to measure the Support construct. Although the two constructs were derived from Gatfield's (2005) proposed framework, the constructs mirrored the way in which other authors have envisioned models of supervision relationships (Boehe, 2016; Brew, 2001; Grover & Malhotra, 2003; Mainhard et al., 2009; Murphy, 2009; Murphy et al., 2007) (Tables 4 and 6). The wording of the questionnaire was slightly altered to create two measurements, the first to collect data from students and the second to collect data from supervisors.

In response to the first research question, the investigation of the questionnaire validity, factor analysis approaches were used. The factor analysis approaches consisted of conducting a CFA to confirm the possible factor structure on which the questionnaire(s) was based, and an EFA was used to consider possible alternative factor structures. During this phase of the study, only the data collected from students were used, given that there were enough records in the data to conform to the statistical assumptions of the analysis. The large sample size also allowed the data to be split into a training dataset for the EFA and a test dataset for the CFA in order to test identified alternative factor structures.

Multiple factor structures were investigated in the analysis (Tables 18 and 29). The CFA found that the modified two-factor model consisting of 24 items and based on the original operationalisation of Structure and Support showed the best overall fit of the data (Table 18), which provided some evidence for the structural and supportive factors as proposed by Gatfield (2005). The model presented good fit statistics, as well as good reliability[52]. Thus, the two-factor model CFA was interpreted to satisfy the requirements of a valid and reliable measurement in response to the first research question. Although given the exploratory nature of the study, some additional findings and limitations during this aspect of the study are worth noting.

During the EFA analysis, similar support for Gatfield's (2005) model was found, where each factor structure contained two factors that could be identified as Structure and Support, respectively. Within the EFA, some of the items initially envisioned to represent structural elements in the supervision relationships may have been viewed as supportive actions from the students' perspectives. Question items initially designed to measure the structure of their relationships loaded strongly only onto factors with support questions. Thus, students may view aspects of structured relationships, such as time invested by their supervisors, as supportive (helping them through the process) rather than structured (project management). As such, students may view a particular action differently compared to how it is perceived by their supervisor, which may affect how supervision relationships are classified (Al-Muallem et al., 2016; Fleming et al., 2013; Orellana et al., 2016; Pearson & Brew, 2002; Pyhältö et al., 2015). Such cross-loadings are not uncommon in research on supervision (Pearson & Kayrooz, 2004). Thus, it becomes essential to reiterate the central role of theoretical frameworks as a guiding framework during the validation process.

Despite the acceptable fit statistics and evidence for the structure and support constructs, the instrument displayed some limitations. These limitations were primarily regarding reverse-scored questions and discriminant validity. Within the factor analysis stage, none of the conceptualised negative questions loaded sufficiently onto either structure or support constructs. These questions formed the focus of a third factor identified in the EFA, which was interpreted as student independence. Where these items were intended to display students' preferences for less structure, they instead seemed to combine into a construct unrelated to either Structure or Support. Herrmann and Wichmann-Hansen (2017) similarly found a three-factor structure focused on Interpersonal relationships (support), Structure and control (structure), and the Promotion of independence and initiative (independence). Although in their study, the concept of increased independence was negatively related to the structural

[52] See section 5.2.1 for the model fit, and section 5.2.2 for the reliability analysis.

component and slightly positively related to the supportive component (Herrmann & Wichmann-Hansen, 2017). Mouton et al. (2015) also argued for an additional construct that represented the locus of decision-making for students, although according to their argument, this formed part of the structural factor.

In contrast to both studies, the current results suggest that the Independence construct was separate from both Structure and Support. The third factor may have developed due to the phrasing of the items, given that the questions shared a focus on independence. As such, from the current findings, students' sense of independence may have been related to their ownership of their work, rather than a desire for increased distance or less involvement from their supervisors. Although this model was not the focus of the analysis moving forward, investigating the role of students' perceived independence would likely be beneficial for future research (Fleming et al., 2013).

The second limitation was that of the instruments' discriminant validity. Within the analysis, there seemed to be a significant overlap between the proposed Structure and Support constructs. The Structure and Support constructs were moderately to strongly correlated within each identified factor structure. This was again found in later correlations within the analysis chapter for both the students and supervisors (Figures 37, 44, and 48). This correlation may be related to the randomisation of the questions during the data collection, which is known to affect the discriminant validity of research instruments through the increase of inter-construct correlations (Podsakoff et al., 2003).

However, this correlation between the structure and support constructs is not isolated to the current study. Scatterplots presented in the results of Fourie (2015, p. 8) and Gedamu (2018, p. 70) suggest a similar relationship between Structure and Support as conceptualised by Gatfield (2005). Al-Muallem (2018) found a moderate correlation between Supervisory skills (comparable to Structure) and Professionalism (comparable to Support). As envisaged by Mainhard et al. (2009), the subscales intended to measure Proximity and Influence also correlated to a greater extent than the authors expected. The results presented by Fleming et al. (2013) showed that all of the subscales in their measure were moderate to strongly correlated for both mentors and mentees. In contrast, however, the study previously discussed by

Wichmann-Hansen and Herrmann (2017) did not display a significant correlation between their conceptualisation of Hands-on supervision (Structure) and Interpersonal relation (Support). This may suggest that such correlations can be instrument or context-specific.

Nonetheless, there seems to be evidence that structural and supportive elements are related, or at least perceived to be related, on the part of students. This finding may somewhat support conceptualising supervision relationships on a single axis. However, given that both structure and support were positively related, this finding contradicts the suggestion that such an axis would distinguish between the tasks needed to complete a qualification (Structure) or focusing on students as people with developmental needs (Support) as the two extremes (Franke & Arvidsson, 2011; Vilkinas, 2008). Instead, supervisors may be classified as either active or hands-on, as opposed to inactive or hands-off, as was proposed by Sinclair (2004), where the two concepts of structure and support may form subscales to measure supervision involvement.

Although the above arguments present possible avenues for future research, the current study used the two-factor model modified through the CFA process. The results indicated that the validity and reliability were acceptable for the exploratory nature of the current research. As such, students' and supervisors' preferred supervision styles could further be explored as conceptualised in Gatfield's (2005) model of supervision. Responses to the relevant Likert-type items were averaged to form indices representing the structure and support constructs. The indices were used in the analysis presented in Chapter Six to respond to the remaining research questions.

7.3. Supervision style preferences of master's and doctoral students (RQ 2)

Is there a difference between the supervision style preferences of master's and doctoral students?

The results presented in this study suggested that students studying towards a master's or doctoral degree typically preferred supervision relationships characterised by higher structure and support. On average, student preferences towards both the structure and support constructs were higher than the scale mid-point, where the contractual supervision style was most often identified. This finding was not isolated to students studying within an ODeL context. Previous research suggested that students preferred contractual supervision (Khosa et al., 2019) or perceived supervisors as ‘good’ who were involved in their students’ studies related to higher structured and supportive relationships (Ali et al., 2016). Within the master’s and doctoral supervision literature, students also reported that they experienced their supervisors as highly structured and supportive, which may suggest that they perceived their supervisors as involved in their studies (Cornér et al., 2017; De Kleijn et al., 2012; Fourie, 2015; Gedamu, 2018; Mainhard et al., 2009; Wichmann-Hansen & Herrmann, 2017).

The focus of the second research question was to determine whether master’s and doctoral students had different preferences toward supervision styles. Within the literature, master’s and doctoral qualifications were associated with requirements for students to participate in independent research under supervision (Zewotir et al., 2015). One of the primary differences or distinguishing features between the two levels of study is that doctoral candidates are required to produce knowledge that is new or novel (Council on Higher Education, 2013b). However, the requirement to produce new knowledge appears to permeate master’s education through the more recent expectation that students publish from their completed studies (Essop, 2020; Jones, 2013; Unisa, 2021). As such, this study aimed to confirm whether students studying for master’s or doctoral qualifications had different preferences for supervision styles.

The median scores for master’s and doctoral students on the structure and support seven-point scales in this study differed between 0.1 and 0.2. A statistically significant difference was found between the scores of master’s and doctoral students. However, the effect size was extremely low, and tests for statistical significance are notoriously oversensitive with larger sample sizes (see section 4.8.1). In response to the second research question, it is argued here that there is no practical difference between master’s and doctoral students’ preferences for supervision styles. A similar argument was made by Lessing and Schulze (2002), where the authors found that master’s and doctoral students held similar perceptions about their supervisors.

It should be noted that although students’ preferences may be similar, their supervision experiences may differ due to their qualifications. Fourie (2015) found that, on average, students studying for a master’s level qualification received less structure and support than students studying for a doctorate. This difference was more apparent when distinguishing between master’s by coursework and full research master’s (ibid.). Students studying for a coursework master’s indicated the lowest levels of structure and support needs from their supervisors (classified as Laissez-faire). In contrast, students studying for a full research master’s experienced more structure and slightly more support (classified as Directional). Those studying for doctoral degrees reported comparably higher levels of structure and support than either master’s level qualifications (classified as Contractual) (Fourie, 2015). It may thus be possible for students to have similar expectations from their supervisors, but that they may have different experiences depending on the qualification for which they enrol. Further comparisons were thus made between student preferences for structure and support, and factors that may affect their supervision style preferences, as expanded on below.

7.3.1. Further exploration of factors that affect students’ preferences

Students’ supervision style preferences were explored outside of the formal research questions in order to gain a broader understanding of what may affect students’ preferences for structure or support in their supervision relationships. Three broad factors were used to compare students’ preferences regarding the amount of structure or support in their supervision relationships. These factors included students’ qualification types (master’s by coursework, full research master’s, and doctoral degrees), completion status (students who have completed compared to those in the process of studying), as well disciplinary differences (comparisons made across different Unisa colleges).[53]

Within the current study, students in all three **qualification types** held similar preferences for structural components in their qualifications. This was the case even though students in coursework master’s typically already have more structure-based qualifications, and doctoral candidates ideally need to become more independent in their work (see section 2.1). Furthermore, students registered for coursework master’s indicated a slightly lower preference for supportive traits. On average, students

[53] Within Unisa colleges represent different faculties.

registered for either full research master's or doctoral qualifications had similar scores for this preference. The effect size found for this comparison was low, and did not show any meaningful differences resulting from the qualification type.

Findings presented by Ali et al. (2016) suggest that students may want more structure or support as a proxy for more involved supervisors rather than dependence. Their findings show that students expected supervisors to be interested and provide feedback on time, be friendly and approachable, and promote independent work at the required level (Ali et al., 2016). In addition, Fourie (2016) found that students reported experiencing different amounts of structure and support depending on their level of study and qualification type. Students enrolled in higher-level qualifications (which carry higher subsidies) reported experiencing more structure and support from their supervisors and institutions. This may suggest that students receive increased involvement from their supervisors based on their qualifications and that their supervisors' level of involvement may not relate to the supervision style preferences of students.

Student respondents who were **still enrolled** in master's or doctoral studies seemed to hold similar preferences towards structure and support as those who had **already completed their qualifications**. The study found that the differences between the scores were statistically significant, but the effect size again suggested that any differences were negligible.

Students who had completed their studies indicated a slightly lower need for structure and support. Although, again, the practical significance of this finding was negligible, as students who completed their studies and those still enrolled held similar supervision preferences. It should be noted that this study made use of a cross-sectional survey, and thus could not account for the development of supervision relationships. As students progress through their studies, they may require different levels of structure or support. In addition, supervisors may adapt to match their supervision style to what they believe their students need at a particular time. To further investigate the progress and development of supervision relationships or supervision style preferences throughout master's or doctoral studies, a longitudinal approach would be required.

Finally, despite disciplinary differences previously found in how supervision is conducted (Mouton et al., 2015; Wichmann-Hansen & Herrmann, 2017) or prioritised (Halse & Malfroy, 2010), the results of the current study found that student preferences were remarkably similar across **colleges**. Although there were significant differences between the colleges that scored the lowest and highest regarding the support construct. Colleges that scored the lowest for support (Mdn = 4.8 – 5) related to Business, Accounting, or Law, whereas those that scored the highest need related to the Natural Sciences, Education, or STEM fields (Mdn = 5.6 – 5.8). Arguably the different needs in support may be due to the resource intensity of the field of study, as opposed to areas where fewer resources may be required to conduct research. Again, the effect size for this analysis was small, which places the practical significance of the differences in questions. As such, the findings from student preferences support arguments that supervision may be similar across disciplines (Connell, 1985; Sverdlik et al., 2018), regardless of disciplinary differences in research methodology.

Ultimately, student preferences were found to be relatively stable across different factors, particularly between master's and doctoral students (that respond to the second research question), but also completion status and colleges. Where significant differences were present, the practical significance suggested that factors had small effects, if any. It was nonetheless interesting to find different preferences between students studying for a master's by coursework versus those studying towards a full research master's or a doctorate. This suggests that students who attend coursework sessions would have different experiences and expectations of their supervision compared to students who do not.

7.3.2. Relationship between the supervision style preferences of master's and doctoral students, and their time to completion (RQ 2.1)

Is there a relationship between the supervision style preferences of master's and doctoral students and their time to completion?

Students' time to completion was explored within the analysis of the student data. The first purpose of this exploration was to provide an overview of how long students study. The second was to investigate whether there was a relationship between how long students studied and their preferred supervision styles. Overall, master's and doctoral students within the sample studied for similar lengths of time, as reported in the literature (within a couple of months difference), suggesting that the findings may be replicated elsewhere.

Master's students in this study **completed their qualifications** within just over three years (Mdn = 3.3 years; M = 3.7 years). This was slightly longer than the two to three years in South Africa (Council on Higher Education, 2009a; Zewotir et al., 2015). This was roughly six months longer than the estimated time reported by Zewotir et al. (2015), and just under four months longer than reported by the CHE (2009a). However, the completion time for master's students in this study was similar to the findings for Unisa students enrolled in 2005, where the average reported time was 3.8 years (Council on Higher Education, 2009a). This completion time was also similar to what was previously reported in Uganda (Wamala & Oonyu, 2012).

Doctoral candidates in the current sample completed their qualifications in just under five years (Mdn = 4.5 years; M = 5 years). These findings were consistent with previously reported times within the context of South Africa, which typically ranged from 4.4 to 4.9 years (ASSAf, 2010; Council on Higher Education, 2009a; Mouton, 2007; Van Lill, 2019). This finding was also consistent with the previously reported results of Unisa, where doctoral candidates completed on average within 4.8 years (Council on Higher Education, 2009a). Additionally, the time to completion found for doctoral candidates within the current study was similar to those reported internationally. Several reported results indicated that it takes doctoral candidates around five years to complete their qualifications; in Uganda (Wamala & Oonyu, 2012); Netherlands (Van de Schoot et al., 2013); the US (Sowell et al., 2015); and Australia (Jiranek, 2010; Sinclair, 2004). In turn, some studies showed shorter completion times; between 3.5 and 4.5 years in Europe (Hasgall et al., 2019); and 4.4 years in New Zealand (Spronken-Smith et al., 2018). One study from the US showed that students might take just under six years to complete their qualifications (5.8 years) (Zhou & Okahana, 2019).

Overall, the completion times for both **qualification levels** were consistent with previously reported times. In both instances, the time to completion was just over two years longer than the minimum qualification timeframes. To compare the time to completion of master's and doctoral students, each recorded time to completion was reduced by the minimum qualification time[54] (Palmer, 2016). The new weighted average and median times indicated that the completion time for master's students was typically three months shorter than for doctoral candidates, although no significant differences were found. As such, the weighted time to completion was equivalent across both qualification levels.

However, it should also be noted that students completed coursework master's qualifications in significantly less time (by around six months) than either full-research master's or doctoral students. This finding may support the argument that coursework studies improve students' time to completion (Geven et al., 2018; Naidoo, 2015; Sverdlik et al., 2018; Watson, 2008). However, to contextualise this finding, the students who completed a master's by coursework nonetheless took on average two years longer than their minimum qualification time. This suggested that more structured qualifications may have limited benefit in lowering the time to completion of master's students.

Students' time to completion was **correlated with their supervision style preferences** to determine whether there was a relationship between the variables. However, students' preferences towards structure or support did not seem to relate to how much time they spent completing their studies. It seems as though students' preferences and the amount of time they spend on their research are unrelated. This finding suggests that blanket interventions that target student supervision may have a limited impact on how long students are registered for their qualifications.

7.3.2.1. Further exploration of factors that affect student's time to completion

Students' time to completion was further explored so as to identify possible characteristics that may have influenced their progress. The variables included in this analysis could be classified as Situational (employment status, funding source, available time to study) or Institutional (college, supervision allocation, and if students changed supervisors) (see section 2.4).

[54] One year for a master's, and two years for a doctorate (Council on Higher Education, 2009a, 2013b).

7.3.2.1.1. Situational factors

Students' time to completion was compared across available information about their employment status, source of funding, and available time, which formed part of the situational factors. As presented in the literature, it was expected that the student's employment status would affect their time availability and qualification performance (Herman, 2011; Kumar & Johnson, 2019; Leijen et al., 2016; Van Lill, 2019). Van Lill (2019) previously found that unemployed students completed, on average, five months faster than their employed peers. In contrast, the current study did not find significant time to completion differences resulting from the employment status of Unisa students.

In a similar argument relating to students' available time, the respondents in this study were asked **how much time they could dedicate to their studies** in a typical week. It was presumed that students who could dedicate more time to their studies would complete them in less time than their peers. In the current study, students were found to complete in significantly less time if they could spend more time on their studies, albeit the effect size was small. The median differences in the time to completion showed that those students who spent more time on their studies could complete them and qualify within three to ten months less, compared to those who studied for less time per week.

As a proxy for available time, previous research found that students who registered for full-time studies completed in less time compared to part-time students (Spronken-Smith et al., 2018; Watson, 2008). Although in the results by Spronken-Smith et al. (2018), full-time students could complete, on average, two years faster than their part-time peers. In contrast, Wamala and Oonyu (2012) did not find a relationship between time to completion and registration status. This might suggest that other influences may affect students' time to completion. According to this study, time to completion was not influenced by employment status, but rather by how much time students claimed to dedicate to their studies. This finding suggests that the employment status of students may not present a proxy for the amount of time that students have to commit to their studies. Thus, students' responsibilities at home or other factors may have to be explored.

Student funding has previously been found to promote student success (Agné & Mörkenstam, 2018; Geven et al., 2018; Jiranek, 2010; Spronken-Smith et al., 2018;

Van Lill, 2019). Within the literature, a lack of available funding was related to dropout considerations (ASSAf, 2010; Castelló et al., 2017; Sverdlik et al., 2018; Van Lill, 2019). In addition, available funding seemed to assist students in completing between six months (Spronken-Smith et al., 2018) and a year (Jiranek, 2010) or two years (Agné & Mörkenstam, 2018) faster than unfunded students. The current results did not seem to support the previous findings. Somewhat consistent with Wamala and Oonyu (2012), the study did not find a significant relationship between time to completion and students' funding sources. Although no significant differences were found in the time to completion of students with various funding sources, it is relevant to note that the small sample of students (n = 22) who indicated multiple funding sources took at least seven months (median) longer than their peers. Thus, students with unstable funding sources may experience delays in their studies, which would take longer than the minimum qualification time. As such, it may be relevant for future studies to consider a more disaggregated perspective of the financial needs of students, and their access to funding, particularly given that fewer than half of the respondents who completed their studies indicated that they were entirely self-funded.

7.3.2.1.2. Institutional factors

Disciplinary differences in master's and doctoral education have received considerable attention within the literature. Studies have found evidence to suggest that there were disciplinary differences in time to completion (Jiranek, 2010; Sinclair, 2004; Sowell et al., 2015; Van Lill, 2019; Wamala & Oonyu, 2012). Such differences typically ranged between three and eleven months (ASSAf, 2010; Council on Higher Education, 2009a; Jiranek, 2010; Van Lill, 2019), although, in other studies, such differences have been up to a year (Sowell et al., 2015; Zhou & Okahana, 2019). Although disciplinary differences in the literature seem to be substantial, the time to completion of doctoral candidates in these studies was, on average, five years (Sowell et al., 2015; Zhou & Okahana, 2019).

The current study found moderate support for the abovementioned literature. A significant difference was found in the completion time of students who studied through different **colleges** (as a proxy for disciplinary difference). However, upon further investigation, it seems this difference was primarily driven by the difference in completion times in the two colleges. Students registered through the College of the Graduate School of Business Leadership completed their studies 23 months after their minimum qualification time. In contrast, those registered through the College of Law took 42.5 months longer than expected. Students in the other colleges took on average 32-36 months longer than their qualifications' minimum time to complete their studies. The abovementioned results imply that discipline has limited influence on time to completion, which does not support the findings from the literature as presented above.

Comparisons of institutional factors were further made regarding how students' **supervisors were allocated** and whether students changed supervisors during their studies. Given the importance of student supervision, as stated in the literature, it may be presumed that the way in which relationships start may affect students' progress or success (ASSAf, 2010; Leijen et al., 2016; Van Lill, 2019). In particular, previous studies have highlighted the positive effects for students involved in the selection of their supervisors, such as the likelihood of completion (Ives & Rowley, 2005; Sverdlik et al., 2018), increased student satisfaction (Ives & Rowley, 2005), or integration into the research community and level of confidence (González-Ocampo & Castelló, 2019). In essence, both students and supervisors need to feel involved in the assignment process (Ives & Rowley, 2005). Within the current study, such benefits did not seem to extend to shorter completion times. No significant differences were found between students regarding how their supervisors were selected (i.e., allocated by the university, personally approached, or where supervisors were recommended).

However, students who **changed their supervisors** seemed to take a median of a year longer with their studies than those who did not. The difference was statistically significant, albeit with a small effect size. Students who changed their supervisors seemed to 'lose' a minimum of two months in their progress, and as such, the process significantly delayed student completion. However, changing supervisors, and the resulting delay, may nonetheless be more beneficial than the alternatives, presumably that students drop out of their studies. This finding may partially support the results of Ampaw and Jaeger (2012), who found that staff turnover did not seem to affect the completion of doctoral candidates. The variation in the delay may result from how the students manage each situation and the new supervisors, as described by a respondent in the study by Ives and Rowley (2005).

7.4. Supervision style preferences of supervisors

The preferred supervision relationships of the supervisors who responded to the survey were typically characterised by higher structure and support, as found among the student respondents. For most supervisor respondents, the contractual supervision style could be identified by high structure and high support scores. At the same time, 20% of the supervisor respondents seemed to have a preference for the directional supervision style. Thus, the supervisors preferred higher structure and support relationships, although this preference was slightly more pronounced towards higher structure scores.

Similar findings were presented in the literature. Khosa et al. (2019) reported that supervisors typically preferred contractual supervision, followed by a preference for directional supervision. The survey results by Mouton et al. (2015) also proved that supervisors preferred relationships that could be characterised as contractual. Supervisors tended to prefer relationships where they could monitor their students (related to structure) and provide high degrees of support, described as collaborative relationships (Mouton et al., 2015). Given the increased push toward focusing on student success and efficiency within master's and doctoral education, this preference for increased involvement with students' studies is not surprising (Mouton et al., 2015). This increased involvement was already presented as part of the thick training model that uses increased structure in training programmes (Mouton, 2011). This furthermore provides evidence that institutional factors influence supervisors in the way that they supervise their students (Khosa et al., 2019). Nonetheless, a preferred supervision style could be identified within the supervision population (Ali et al., 2016; Benmore, 2016; Gatfield, 2005; Lessing & Schulze, 2004; Marshall et al., 2017; Mouton et al., 2015; Roach et al., 2019; Sinclair, 2004; Vilkinas, 2008).

7.4.1. Factors that influence supervisor preferences (RQ 3)

Which factors influence the supervision style preferences of master's and doctoral supervisors?

The third research question concerned the possible factors influencing supervisor preferences toward structure or support. In response to this research question, supervisor preferences were compared across several available variables, which included supervisors’ highest qualifications, internal or external supervision status, disciplinary differences, willingness to adapt, the level of attention they provide to their students, and self-reported supervision loads.

The **highest qualification** of supervisors was interpreted as a possible indication of their experience in supervision in higher education. Comparing supervisors’ preferences for structure or support between respondents whose highest qualification was a master’s and those who had obtained a doctorate showed no significant differences. This finding seems to contradict Boehe’s (2016) claim that a higher level of expertise would result in higher levels of support. Or that more experienced supervisors would display higher levels of structure (Manyike, 2017). However, such arguments remain tentative, given that both cited authors referred to relationships rather than supervision style preferences.

Supervisors who were **not internally appointed** within Unisa did not seem to have a different structure or support preferences compared to supervisors appointed within the institution. This finding may suggest that the results from the current study could be applied outside the ODeL context. However, more research would be required to provide evidence for such a claim.

Disciplinary differences were investigated by comparing supervisors’ preferences across different colleges, similar to the analysis of the student data. The findings suggest that there were some differences between supervisors of different colleges, which seemingly support previous studies that have been conducted (Mouton et al., 2015; Wichmann-Hansen & Herrmann, 2017). Respondents from the College of Agriculture and Environmental Sciences, and Science, Engineering and Technology, seemed to prefer supervision styles with higher structure and support. The College of Law seemed to indicate a lower comparable preference for supportive elements within their supervision relationships. However, the differences in supervisors’ preferences were primarily between the colleges with the highest averages compared to those with the lowest. No other noteworthy differences in preferences for structure or support were found between any of the other disciplines. This may suggest that supervision tasks may be more homogeneous across different disciplines (Connell, 1985; Sverdlik et al., 2018), although with some differences due to their research contexts. Furthermore, in all colleges, supervisors tended to rate their preferences for structure or support higher than the scale midpoint. It remains debatable as to whether supervision can be considered a shared skill across disciplines (Anderson et al., 2006; Connell & Manathunga, 2012; Halse & Malfroy, 2010; Lovitts, 2008; Vilkinas, 2002).

Most of the supervisors indicated that they would **change their supervision styles** based on the needs of their students. This finding seemed to support the view that supervision may be more individualised and influenced by student needs (Gatfield, 2005; Kumar & Johnson, 2017, 2019; Schulze, 2011; Vilkinas, 2008). Supervisors might adapt their approaches even if they do not prefer a particular interaction style (Kumar & Johnson, 2017, 2019; Murphy, 2009; Schulze, 2011). Each relationship could be considered unique (Anderson et al., 2006). However, the current study also found a weak but significant positive correlation between supervisors' willingness to adapt and their preference for higher structural and supportive relationships. Supervisors who prefer contractual relationships are seemingly more willing to change based on the needs of their students. This may be due to being more involved in their student's academic journeys.

Supervisors who preferred higher structure and support were also more likely to agree that they could typically **give enough attention to their students**. A significant positive correlation with a moderate effect size was found between supervisors' rating of their attentiveness and their preferences for structure and support. This may relate to the idea that supervisors who prefer higher structure and support would be more involved in their student's academic journeys and may thus feel that they were able to give enough input when needed. To some extent, this finding supports the theoretical perspective of Boehe (2016) that more attentive supervisors would be more supportive.

Supervisors' ability to attend to their students depends on their **supervision loads** and perceived supervision capacity. In this study, supervisors who held doctoral qualifications were reportedly responsible for seven master's and doctoral students simultaneously (median). This was consistent with previously reported findings by the Council on Higher Education (2009a) that supervisors were responsible for seven students on average. Most of the supervisors in this study were responsible for between one and ten students at the time of data collection. Three of the students would typically be studying for a doctoral degree. This finding was in line with what was reported by Mouton et al. (2015), who found that South African supervisors were on average responsible for four doctoral candidates at a time. As previously described, supervisors are under increasing pressure to provide evidence of student progress, which requires more administration (Hasgall et al., 2019; Mouton et al., 2015). As a result, supervisors' preference for contractual supervision may signal that they are taking a stronger leading role in their students' work (Deuchar, 2008) to ensure students' progress. However, in the long term, a stronger leading approach may interfere with students' autonomy and independence, which are required of students who have completed their qualifications (Deuchar, 2008; Owler, 2010).

The supervision style preferences of supervisors seemed to indicate a tendency towards preferring contractual or at least more directive supervision. Neither the level of qualification nor contract status seemed to affect supervisor preferences, although slight differences were found between different colleges. Supervisors who tended to be more involved with their students, either through their willingness to adapt their process, or feeling they could attend to each student's needs, seemed to positively relate to their scores for structure and support.

7.5. Relationship between the congruence of supervision relationships and the time to completion (RQ 4)

Is there a relationship between the congruence of supervision relationships and the time to completion of master's and doctoral students?

The focus of the final research question was to investigate if there was a relationship between the congruence of supervision relationships and the time to completion of master's and doctoral students. For this comparison, the structure and support scores for students and supervisors were subtracted to form combined scores for each construct representing individual relationships. On average, the supervision style preferences of students and their supervisors tended to be congruent. On average, the calculated score difference was close to zero, although not all the respondent dyads had similar preferences toward structure or support. It is also noteworthy that the analysis did not find a statistically significant difference between the relationship congruence for either construct when comparing the scores between students who had completed their degree, or were still in progress. This finding may thus suggest that student completion has a limited effect on perceived congruent relationships.

In response to the final research question, the study was unable to find evidence to suggest that congruent supervision relationships lead to faster time to completion for master's and doctoral students. Although the study sample could be considered small at this point in the analysis, the tests were insignificant, and the correlation coefficients were negligible for both structure and support. This finding thus did not support previous literature suggesting that supervisor relationships would affect students' time to completion (Fourie, 2016; Jones, 2013; Murphy, 2009; Roach et al., 2019; Sinclair, 2004; Van Lill, 2019).

7.6. Limitations and Further Research

The following section addresses some of the limitations experienced in this study and recommendations for possible research. Future projects ought to consider **how the supervision relationships are measured**, and whether survey responses provide the best insight into how such unique relationships may be classified or described. Alternatively, naturalistic research methods may provide deeper insight into the experiences and unique circumstances of both students and supervisors. The limitations of the current project revolve around the cross-sectional survey design, the limited sample size, the research instrument, and available data for research on supervision relationships.

The **cross-sectional** nature of the project meant that it was not possible to investigate the development of supervision relationships. Although the survey included a self-report question to ask supervisors if they adapt their supervision styles, a longitudinal study will provide more insight into the changes that occur over time. Such result may differ from those presented in the current project.

Although the student **sample within this study** is arguably representative of the study population, the sample for supervisors and, more importantly, the sample of the combined relationships were too small to generalise the current findings. Thus, the supervisor sample may have been biased towards the contractual supervision style preference. More research is needed to support the findings from the current study. It may be beneficial to ask students to express how they experience their supervision relationships, rather than asking after their preferences. This would only provide the student perspective. However, students may be more able to reflect on their unique relationships. At the same time, supervisors have multiple supervision relationships that may not all be classified similarly. This would require adapting the tools to ask students about the extent to which activities are present or prevalent within their relationships with their supervisors (Fourie, 2015).

Despite the strong focus on validating the **research instrument**, several aspects of the process can be improved in future studies. The first is to acknowledge that the factors that formed the basis for the measurement indices were only investigated from the student's perspective. As such, supervisor responses may provide different factor structures (Al-Muallem et al., 2016; Ali et al., 2016; Orellana et al., 2016). At the same time, using Item Response Theory (IRT) may be valuable for future validation processes. The identified Independence construct may also be an area for further investigation (Fleming et al., 2013; Jones, 2013) that can be argued to form part of the Exogenous variables in Gatfield's (2005) model.

The second limitation related to the validation concerns the **number of items excluded** from the instrument. Over half of the instrument items were removed throughout the validation process, which was more than the 20% limit proposed by Hair et al. (2014). Future studies could thus further improve the research instrument by adapting question items to relate more strongly to each factor of interest. This includes limiting the response scale range to five options, rather than seven. In addition to not reverse scoring, or randomising question items, which may have affected the discriminant validity of the instrument (Podsakoff et al., 2003).

Through the investigation of how available variables affect students' time to completion, the results in this study seemed to be consistent with past research with similar foci. Despite finding some significant relationships or differences in students' time to completion, the effects were typically small. Students still took up to two to three years longer than their minimum qualification time to complete their studies. In their article, Orellana et al. (2016) argued that it may be more relevant to include the interests and abilities of the students so as to ensure that the broader educational context is included in such analysis. Consistent with this argument, future studies may

explore alternative factors influencing students' success (such as Gatfield's (2005) exogenous factors see Table 3) and time to completion.

A possible source of such factors may be institutional data related to supervision relationships. The current study was limited to the collected data that could be linked to institutional records. Future studies could investigate possible differences between supervisor characteristics, by linking available supervisors' data with various student success criteria, including time to completion, student retention, and throughput, available from institutional records. Data cleaning and sample sizes, may be central concerns for using institutional data, given that it is not always possible to record complex curriculum changes in structured databases, and there may not be enough graduate records to utilise advanced analytical techniques. However, it may be argued that exclusively focusing on the supervision relationship is an oversimplification of students' academic journeys.

7.7. Conclusion

This study aimed to investigate whether student-supervisor fit influenced the time to completion of master's and doctoral students. For this thesis, a research instrument was developed and validated to measure the supervision style preferences of master's and doctoral students and their supervisors. The measured preferences for students and supervisors were compared to determine student-supervisor fit, which was correlated with master's and doctoral students' time to completion. The results of this thesis did not find a relationship between the time to completion of students and the fit between students' and supervisors' preferences towards structured or supportive supervision styles.

The findings within this study provide a novel interpretation of the role of supervisors regarding students' time to completion within an ODeL context. This is particularly important given the focus on master's and doctoral education to increase the research capacity in South Africa, and increase participation in the knowledge economy (Cloete et al., 2015; Deuchar, 2008; Laher et al., 2019; Mouton, 2011).

The study found that supervision relationship fit between students and their supervisors did not seem to influence students' time to completion. Students whose supervision style preferences matched closely with the supervision style preferences of their supervisors did not complete their studies in less time. It is possible that students or their supervisors might disengage from their relationships if their preferences did not match, and as a result, supervision relationship fit might affect student throughput, dropout, or supervision changes, rather than time to completion.

The resulting interpretation from this finding suggests that increasing managerialism in higher education to improve efficient completion times would not have the desired effect. If supervision fit influences student throughput rather than completion time, then the increased managerialism to artificially mediate supervision relationships may rather increase student dropout, which would be counterproductive.

Supervision relationships are ultimately complex. It is not clear whether any of the presented theories manage to capture a useful representation of how supervision relationships can be understood, particularly in an ODeL context. The most useful abstraction of supervision relationships may be that supervisors become more involved, or less involved in their students' projects (Sinclair, 2004). Within this thesis supervisors who were more willing to adapt to their students' needs, or were able to spend sufficient time guiding their students, were also more likely to indicate stronger preferences for structured and supportive relationships. As such, structure and support might not be measured on independent scales, but rather form sub-sections within a larger measurement of hands-on or hands-off supervision approaches (Sinclair, 2004). Alternatively, the high correlations between structure and support may rather stem from the subjective nature of self-report instruments. As such, the theoretical framework may function as intended if data is sourced from alternative records (i.e. number of meetings held, rather than reporting a preference for regular meetings). Similarly, asking students the extent to which supervision activities occur during their academic journeys may provide an alternative evaluation of supervision relationships that seemed to have been beneficial in previous research (Fourie, 2016).

Master's and doctoral students shared similar supervision style preferences. In addition, students' preferences were similar to those of the supervisors, which may suggest that supervision style preferences form early within research training, or may already be formed by the time students register for a master's. Although supervisors may initially depend on their personal experiences of being supervised to inform how they fulfil their roles (Kumar & Johnson, 2017; Lee, 2007; Vereijken et al., 2018), it is possible that they already have a preference for a particular supervision style. Instead, the supervision experiences of supervisors may provide them with a reference point or example to understand these preferences. Effectively making use of their previous experiences to articulate their supervision style preferences.

As a result, it becomes problematic to assume that students can supervise once they have completed their studies. Recent graduates would likely have various supervision experiences, and examples of what they felt worked or did not work, but may not have the necessary experience to recognise effective supervision practices. This is already being addressed in the higher education sector, where supervisors are required to undergo training before being allocated students to supervise. Such initiatives should focus on training supervisors on how to navigate complex relationships rather than a set of procedures to be followed. This could likely be applied to both master's and doctoral education. Consistent with the assumptions made in this thesis, the evidence suggests that supervision was similar in both master's and doctoral education, where differences between the two qualification levels would likely relate to the project scope, depth, and complexity.

In this study, and the literature review, only a few of the investigated variables seemed to have any meaningful impact on students' time to completion, if at all. It also remains unclear which aspects of students' academic journeys affect their throughput, or the possibility of dropping out. Although it may be an intuitive conclusion, the amount of time that students spend on their studies per week seems to be related to how quickly they were able to complete them, albeit with a limited effect. However, students' employment status may not be an accurate indication of how much time they have available for their studies. Rather, there may be value to investigating how students manage their time in master's or doctoral education, given the time commitment required for such qualifications.

Finally, when considering the high proportion of dropouts reported in the literature, there may be more value in investigating how to decrease student attrition. A significant proportion of resources are lost when students are only partially trained, where increasing successful qualification completion would increase supervision capacity, which is a pre-requisite for improving the efficiency of both master's and doctoral training.

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Appendix A: Likert questions

Table 71: Research instrument

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_01	Structure	Accountability and Stages	Contractual arrangement	I set up a formalised agreement between myself and my students that stipulate our shared roles and responsibilities during the supervision	I would want my supervisor to set up a formalised agreement between us to stipulate shared roles and responsibilities during the supervision process	+
Q_02			Deadlines	I have fixed deadlines for the submission of students' work	I would prefer to have fixed deadlines for the submission of my work	+
Q_03			Established timeframes	I try to keep my students to their stated timelines as much as possible to minimize the possibility of taking longer with a project	My supervisor should try to hold me to my stated timelines to minimise the possibility of taking longer with a project	+
Q_04			Independence	My students work independently without having to account for how they spend their time	I should be able to work independently without having to account for how I spend my time	-

[55] Question items that indicate a negative phrasing were envisioned to be reverse scored in the final model.

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_05			Staged write-up	During the supervision process we establish rigid milestones that students need to achieve before they are able to progress to the following stages of their projects	I would prefer to have established rigid milestones that need to be achieved before moving to the following stages of my project	+
Q_06			Standard of work (benchmark)	I explain to my students the required standard of work expected of them early within the supervision relationship	I would need to understand the standard or work expected as early as possible within the supervision relationship	+
Q_07			Supervisor turnaround time	I do not have a predetermined schedule for student feedback, I provide student feedback when I am able to engage with their work	Supervisors should not work on a predetermined schedule for feedback, they should provide feedback when they are able to engage with the work	-
Q_08			Timely feedback	Most of the time I provide feedback on my students' work within the timeframe determined within our supervision relationship	I should always receive feedback within the time-frame determined within our supervision relationship	+
Q_09			Work independently	It is important for students to work as independently as possible, where supervision input is considered as only a suggestion	I prefer to work as independently as possible, where supervision input is considered as only a suggestion	-
Q_10		Organisation	Administration	I prefer to handle most of the administrative queries from my students personally	I prefer to contact my supervisor to handle administrative queries	+

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_11			Change topics (to meet supervisor needs)	I would instruct my student to change aspects of their project to ensure their study remains within the scope of my research area	If required I would prefer my supervisor have aspects of my project changed so that it would remain within the scope of their research area	+
Q_12			Colloquiums and conferences	I try to get my students involved in relevant conferences and colloquiums	Supervisors should assist their students to get involved in relevant conferences and colloquiums	+
Q_13			Consistent contact	I have scheduled regular pre-arranged meetings with each of my students to ensure that we have consistent contact	I prefer to have a pre-arranged regular meeting schedule to ensure that we have consistent contact	+
Q_14			Examination process	I walk each student through the examination process in detail	It is necessary to walk students though the examination process in detail	+
Q_15			Informal structure	I provide my students with a predetermined set structure for their dissertation / thesis	I would need a predetermined set structure to organise my dissertation / thesis	+
Q_16			Intervention	I only intervene in a student’s work if there are serious problems	Supervisors should only intervene in their student’s work if there are serious problems	-

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_17			Progress reports	I regularly follow up on the progress of each student	My supervisor should regularly check up on my progress	+
Q_18			Recording meetings	It is the responsibility of students to keep records of our discussion (complete notes or recordings etc.)	Students should be responsible for keeping records of supervision discussions (complete notes or recordings etc.)	-
Q_19			Setting stages and goals	I assist each student to set milestones and goals for their projects	My supervisor should assist me to set up milestones and goals for my project	+
Q_20			Setting the topic	My students decide on their own research topics	I would prefer to decide on my own research topic	-
Q_21			Supervisor availability	My students are able to call on me for ad hoc meetings whenever they need	I should be able to call on my supervisor for ad hoc meetings whenever I need	-
Q_22			Supervisor input	My students completely control the direction of their projects, with minimal changes in the overall direction from me	I should be in complete control over the direction of my project, with minimal changes in the overall direction from my supervisor	-

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_23			Time flexibility	As long as my students work steadily, they can take as long as is needed to finish their work	As long as I work at a steady pace I should be allowed as much time as I need to finish my work	-
Q_24			Literature review	I actively guide each one of my students on how to conduct a literature review	Supervisors should guide their students on how to conduct a literature review	+
Q_25			Methodologies	I direct my students to use specific methods in their research	Supervisors should indicate specific methods students have to use in their research	+
Q_26			Knowledge / expertise	I prefer to supervise students where I learn with them about a particular problem or research method, opposed to dealing with information I am already very familiar with	It would be better when supervisors learn with their students, and who are not experts in a particular area	-
Q_27			Referencing	I actively guide my student on how to avoid plagiarism in their work	Supervisors should actively guide their students to avoid plagiarism in their work	+
Q_28		Skills provision	Short training seminars	I refer my students regularly for relevant research workshops / seminars for them to increase their ability to conduct research	I would want my supervisor to regularly refer me for relevant research workshops / seminars for me to increase my ability to conduct research	+

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_29			Statistics training (analysis)	Learning how to analyse data is a skill that students need to struggle with on their own	I would prefer to develop the skill on how to analyse my research data on my own	-
Q_30			Time management	I assist my students to set up realistic timelines or research schedules to manage their time on their research effectively	I would want my supervisor to assist me to set up realistic timelines or a research schedule to manage my time on my research effectively	+
Q_31			Writing (/structure)	I regularly need to assist in the actual writing of sections if my students have difficulties, to provide examples for them to follow	My supervisor should provide examples of writing by assisting in the actual writing of sections of my research project	+
Q_32			Funding	I ensure that my students are aware of the requirements and possibilities for funding	Supervisors should ensure that their students are aware of the requirements and possibilities for funding	+
Q_33		Financial	Research funds	My students are funded with money that I am responsible for	Students should be funded through money that their supervisors are responsible for	+
Q_34	Support	Material	Equipment	I make sure that my students have access to all necessary equipment	Supervisors should make sure that their students have access to all necessary equipment	+

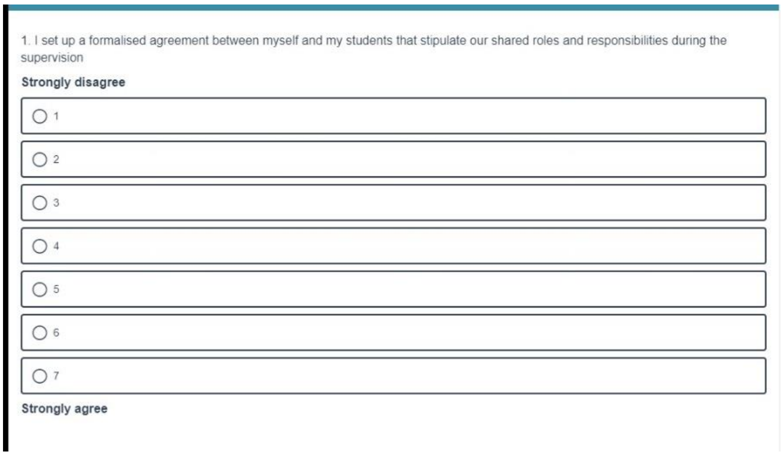
Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_35			Ethics: policy material	My students are required to source the relevant information and procedures of the ethical clearance process on their own, because it forms part of conducting research	I would prefer to source the relevant information and procedures of the ethical clearance process on my own, and only ask for assistance from my supervisor if required	-
Q_36			Office space	I ensure that my students have access to suitable workings space / common rooms at the university / satellite campuses	Supervisors should ensure that students have access to a suitable working space/common room at the university / satellite campuses	+
Q_37			Relevant articles	I provide my students with relevant articles / recommend relevant articles that may be useful for their work	Supervisors should provide / recommend relevant articles to their students that are useful for their work	+
Q_38		Pastoral Care	Communication	I try to keep in touch with my students between our supervision meetings	I should be able to keep in touch with my supervisor(s) between our supervision meetings	+
Q_39			Exposure to academic discipline	I prefer to co-write articles with my students on their work once their projects are completed	Supervisors should co-write articles with their students after the completion of their studies	+
Q_40			Informal meetings	I try to keep my supervision meetings as formalised as possible to ensure that our discussions remain focussed only on the research project	Supervision meetings should be as formalised a possible to ensure that the discussion remains focussed only on the research project	-

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_41			Informal meetings	It is important for my students to view me as approachable	Supervisors should be approachable to their students	+
Q_42			Interactivity	I prefer supervision meetings with my students to only be concerned with gaining clarity on feedback. My students only need to take note of what is discussed and address issues in future submissions	Supervision meetings should only be concerned with gaining clarity on feedback. I would rather only take note of what is discussed and address issues in future submissions	-
Q_43			Interest	I only supervise students who's topics interest me	A supervisor should only agree to supervise my work if they are actually interested in the topic	+
Q_44			Mentoring	I try to include discussions with students on how their research projects might influence their desired professions, as opposed to limiting our conversations to only the completion of their research projects	Supervision should not only focus on the completion of a research project, but also include discussions with students regarding their futures, and how they can fit research into their desired professions	+
Q_45			Persistence / motivation	Students should be able to remain completely self-motivated throughout their studies, without needing encouragement from their supervisor(s)	I would not need constant encouragement from my supervisor to remain motivated throughout my study	-
Q_46			Positive feedback	I frame all of my feedback positively to acknowledge the work that students put into their writing	Supervision feedback should not just criticise the writing of their students, and realise that they work hard to produce a piece of writing	+

Item	Theme	Category	Operationalisation	Supervisor Question	Student Question	Positive or Negative [55]
Q_47			Proactive supervision	I try to anticipate what students will need to do in their projects and guide them to stay prepared	Supervisors should anticipate what will happen next in the projects of their students, and guide them to stay prepared	+
Q_48			Problems assistance	When my students encounter problems I leave them to work out a solution for themselves	When I encounter a problem, my supervisor should leave me to work out solutions on my own	-
Q_49			Sensitivity to candidate needs	I develop personal relationships with my students so that I can be aware of what happens in their lives	You should be able to build a relationship with your supervisor, so that they would be aware of what is happening in your life	+
Q_50			Social	I arrange for my students to interact or work together to assist in supporting each other throughout their studies	Supervisors should arrange for their students to interact or work together to assist in supporting each other	+
Q_51			Two-way commitment	As long as students are committed to their projects it does not really matter if supervisors share their commitment	As long as students are committed to their projects it does not really matter if supervisors share their commitment	-

Appendix B: SurveyGizmo examples

Mobile view



Desktop view

Appendix C: R Libraries

Table 72: R Libraries applied

Library designation	Library description[56]	Library reference
corpcor	"Implements a James-Stein-type shrinkage estimator for the covariance matrix, with separate shrinkage for variances and correlations."	(Schafer et al., 2017) (Field et al., 2012)
dplyr	"A fast, consistent tool for working with data frame like objects, both in memory and out of memory."	(Wickham et al., 2021)
dunn.test	"Computes Dunn's test (1964) for stochastic dominance and reports the results among multiple pairwise comparisons after a Kruskal-Wallis test for stochastic dominance among k groups"	(Dinno, 2017)
ggplot2	"A system for 'declaratively' creating graphics, based on "The Grammar of Graphics"."	(Wickham, 2016)
ggpubr	"'ggpubr' provides some easy-to-use functions for creating and customizing 'ggplot2'- based publication ready plots."	(Kassambara, 2020)
GPArotatio n	"GPArotation implements Gradient Projection Algorithms and several rotation objective functions for factor analysis."	(Bernaards & Jennrich, 2005) (Field et al., 2012)
hrbrthemes	"A compilation of extra 'ggplot2' themes, scales and utilities"	(Rudis, 2020)
imputeTS	"It offers several different imputation algorithm implementations. Beyond the imputation algorithms, the package also provides plotting and printing functions of missing data statistics."	(Moritz & Bartz-Beielstein, 2017)
knitr	"Provides a general-purpose tool for dynamic report generation in R using Literate Programming techniques."	(Xie, 2021)
lavaan	"The R package lavaan has been developed to provide applied researchers, teachers, and statisticians, a free, fully open-source, but commercial-quality package for latent variable modelling."	(Rosseel, 2012)
lavaanPlot	"Plots path diagrams from models in lavaan."	(Lishinski, 2018)
matrixStats	"High-performing functions operating on rows and columns of matrices"	(Bengtsson, 2020)
MVN	"The MVN package contains functions in the S3 class to assess multivariate normality."	(Korkmaz et al., 2014)
pander[57]	"Contains some functions catching all messages, 'stdout' and other useful information while evaluating R code and other helpers to return user specified text elements (like: header, paragraph, table, image, lists etc.)"	(Daróczi & Tsegelskyi, 2021)
psych	"The psych package has been developed at Northwestern University to include functions most useful for personality and psychological research."	(Revelle, 2019)

[56] Quoted sections sourced from program help files, found under "Description:"
[57] Code used in the validation of the research instrument was sourced from https://benwhalley.github.io/just-enough-r/modification-indices.html

Library designation	Library description[56]	Library reference
rstatix	"Provides a simple and intuitive pipe-friendly framework, coherent with the 'tidyverse' design philosophy, for performing basic statistical tests, including t-test, Wilcoxon test, ANOVA, Kruskal- Wallis and correlation analyses."	(Kassambara, 2021)
Stats Tools Package (AMOS)[58]	"The Stats tools package is a collection of tools that I've either developed or adapted for making statistical analysis less painful."	(Gaskin, 2019)

[58] An Excel document that was designed to calculate the reliability of Confirmatory Factor Analysis outputs from IBM® SPSS® Amos. The outputs created by R were adapted to be used for these calculations.

Appendix D: Ethical clearance forms

Ethics Committee of the Department of Psychology

Ref. No: PERC-17062A

UNISA university of south africa
Department of Psychology

Ethical Clearance for M/D students: Research on human participants

The Ethics Committee of the Department of Psychology at Unisa has evaluated this research proposal for a Higher Degree in Psychology in light of appropriate ethical requirements, with special reference to the requirements of the Code of Conduct for Psychologists of the HPCSA and the Unisa Policy on Research Ethics.

Student Name: Mr H H Janse Van Vuuren **Student no.** 48258415

Supervisor: Dr E Archer **Affiliation:** Institutional Research, Unisa

Title of project:

Relationship between Student and Supervisor Fit, and "Time to Completion" in Masters and Doctoral Programmes

The proposal was evaluated for adherence to appropriate ethical standards as required by the Psychology Department of Unisa. The application was approved by the Ethics Committee of the Department of Psychology on the understanding that –

- All ethical requirements regarding informed consent, the right to withdraw from the study, the protection of participants' privacy and confidentiality of the information should be made clear to the participants and adhered to;
- Additional clearance will have to be obtained from the Senate Research, Innovation and Higher Degrees committee to confirm that any and all formal procedures that need to be followed to gain access to the participants and to obtain information for the purposes of research, as required by the institution, have been adhered to, and that the relevant authorities are aware of the scope of the research.

Date of issue: 2017-10-25 *This clearance is valid until 31 December 2021*

Signed:

Papaikonomou

Prof. M Papaikonomou
[For the Ethics Committee]
[Department of Psychology, Unisa]

The proposed research may now commence with the proviso that:

1) *The researcher/s will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.*
2) *Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study, as well as changes in the methodology, should be communicated in writing to the Psychology Department Ethics Review Committee.*
3) *An amended application should be submitted if there are substantial changes from the existing proposal, especially if those changes affect any of the study-related risks for the research participants.*
4) *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.*

Please note that research where participants are drawn from Unisa staff, students or data bases requires permission from the Senate Research and Innovation Committee (SENRIC) before the research commences.

Unisa College of Human Sciences Research Ethics Committee

UNISA university of south africa

UNISA COLLEGE OF HUMAN SCIENCES RESEARCH ETHICS COMMITTEE

26 March 2018

Dear H. H Janse van Vuuren

NHREC Registration # : REC-240816-052

CREC Reference #: 2018 CHS 006

Name : H. H Janse van Vuuren

Student #: 48258415

Decision: Ethics Approval from 26 March 2018 to 01 April 2023

Researcher(s): [redacted] St
Pretoria

Supervisor (s): Dr Elizabeth Archer
University of the Western Cape,
Director of Institutional Research

Working Title

Relationship between student and supervisor fit, and 'time to completion' in Masters and Doctoral programmes

Highest Qualification: Masters of Arts in Research Consultation (Research psychology)

Thank you for the application for research ethics clearance by the Unisa College of Human Sciences Research Ethics Committee for the above mentioned research. Ethics approval is granted for 5 years.

*The **Chair of College of Human Sciences Research Ethics Committee endorsed the application**, on 21 Feb 2018 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(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.

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2. Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study should be communicated in writing to the CREC Committee.
3. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.
4. Any changes that can affect the study-related risks for the research participants, particularly in terms of assurances made with regards to the protection of participants' privacy and the confidentiality of the data, should be reported to the Committee in writing, accompanied by a progress report.
5. The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study. Adherence to the following South African legislation is important, if applicable: Protection of Personal Information Act, no 4 of 2013; Children's act no 38 of 2005 and the National Health Act, no 61 of 2003.
6. Only de-identified research data may be used for secondary research purposes in future on condition that the research objectives are similar to those of the original research. Secondary use of identifiable human research data require additional ethics clearance.
7. No field work activities may continue after the expiry date 01 April 2023. Submission of a completed research ethics progress report will constitute an application for renewal of Ethics Research Committee approval.

Note:

The reference number 2018 CHS 006 should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.

Yours sincerely,

Signature *Mudzusi*
Prof AH Mavhandu-Mudzusi
Chair : CHS Research Ethics Committee
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Research Permission Sub-committee (RPSC) of the Senate Research, Innovation, Postgraduate Degrees and Commercialisation Committee (SRIPCC)

UNISA university of south africa

RESEARCH PERMISSION SUB-COMMITTEE (RPSC) OF THE SENATE RESEARCH, INNOVATION, POSTGRADUATE DEGREES AND COMMERCIALISATION COMMITTEE (SRIPCC)

11 May 2018 (Date of issue)
1 April 2019 (Date of 1st amendment)
22 September 2020 (Date of 2nd amendment)

Ref #: 2018_RPSC_023_AR
Mr H Janse van Vuuren
Student #: 48258415
Staff #: N/A

Decision: Ethics approval from 22 September 2020 until 21 August 2021.

Principal Investigator:
Mr. Hermanus Janse van Vuuren
Department of Psychology
School of Social Sciences
College of Human Sciences
[redacted]

Supervisor: Dr. Elizabeth Archer; [redacted]

Relationship between student and supervisor fit, and 'time to completion' in Masters and Doctoral programmes

Your application regarding permission to extend the study approval period in respect of the above study has been received and was considered by the Research Permission Subcommittee (RPSC) of the UNISA Senate, Research, Innovation, Postgraduate Degrees and Commercialisation Committee (SRIPCC) on 11 September 2020.

It is my pleasure to inform you that permission has been granted for the study. You may:

1. Obtain the list of Unisa supervisors by the staff numbers and the corresponding M&D students and alumni who graduated within the last three years, also indicated by their student numbers. The list may also indicate the work status of the supervisors and their length of service at Unisa, as well as the email addresses of the supervisors and the MyLife email addresses of the students.
2. Be provided with the personal email addresses of Unisa alumni who graduated in the

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last three years.

3. Send an online survey to the supervisors and the students and may also send them one reminder after 2 weeks.
4. Gain access to the following information about the students:

- Qualification code
- Qualification credits
- Qualification minimum time
- Degree type (Limited scope dissertation/full dissertation
- Registration date
- Registration status
- Completion status
- Completion date (if completed).

You are requested to submit a report of the study to the Research Permission Subcommittee (RPSC@unisa.ac.za) within 3 months of completion of the study.

The personal information made available to the researcher(s)/gatekeeper(s) will only be used for the advancement of this research project as indicated and for the purpose as described in this permission letter. The researcher(s)/gatekeeper(s) must take all appropriate precautionary measures to protect the personal information given to him/her/them in good faith and it must not be passed on to third parties. The dissemination of research instruments through the use of electronic mail should strictly be through blind copying, so as to protect the participants' right of privacy. The researcher hereby indemnifies UNISA from any claim or action arising from or due to the researcher's breach of his/her information protection obligations.

Note:
The reference number **2018_RPSC_023_AR** should be clearly indicated on all forms of communication with the intended research participants and the Research Permission Subcommittee.

We would like to wish you well in your research undertaking.

Kind regards,

RVisagie

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Appendix E: Instrument validation

Normality tests

Table 73: Student Likert skewness statistic

	Test	Variable	Statistic	p-value	Normality
1	Shapiro-Wilk	Q_01	0.8623	<0.001	NO
2	Shapiro-Wilk	Q_02	0.8672	<0.001	NO
3	Shapiro-Wilk	Q_03	0.8391	<0.001	NO
4	Shapiro-Wilk	Q_04	0.9085	<0.001	NO
5	Shapiro-Wilk	Q_05	0.8988	<0.001	NO
6	Shapiro-Wilk	Q_06	0.7268	<0.001	NO
7	Shapiro-Wilk	Q_07	0.9058	<0.001	NO
8	Shapiro-Wilk	Q_08	0.7897	<0.001	NO
9	Shapiro-Wilk	Q_09	0.9318	<0.001	NO
10	Shapiro-Wilk	Q_10	0.9135	<0.001	NO
11	Shapiro-Wilk	Q_11	0.9042	<0.001	NO
12	Shapiro-Wilk	Q_12	0.8042	<0.001	NO
13	Shapiro-Wilk	Q_13	0.8591	<0.001	NO
14	Shapiro-Wilk	Q_14	0.8324	<0.001	NO
15	Shapiro-Wilk	Q_15	0.8451	<0.001	NO
16	Shapiro-Wilk	Q_16	0.9021	<0.001	NO
17	Shapiro-Wilk	Q_17	0.8167	<0.001	NO
18	Shapiro-Wilk	Q_18	0.8122	<0.001	NO
19	Shapiro-Wilk	Q_19	0.8857	<0.001	NO
20	Shapiro-Wilk	Q_20	0.8747	<0.001	NO
21	Shapiro-Wilk	Q_21	0.8884	<0.001	NO
22	Shapiro-Wilk	Q_22	0.9404	<0.001	NO
23	Shapiro-Wilk	Q_23	0.9264	<0.001	NO
24	Shapiro-Wilk	Q_24	0.8188	<0.001	NO
25	Shapiro-Wilk	Q_25	0.9021	<0.001	NO
26	Shapiro-Wilk	Q_26	0.9184	<0.001	NO
27	Shapiro-Wilk	Q_27	0.7698	<0.001	NO
28	Shapiro-Wilk	Q_28	0.8035	<0.001	NO
29	Shapiro-Wilk	Q_29	0.8808	<0.001	NO
30	Shapiro-Wilk	Q_30	0.8552	<0.001	NO
31	Shapiro-Wilk	Q_31	0.895	<0.001	NO
32	Shapiro-Wilk	Q_32	0.7268	<0.001	NO
33	Shapiro-Wilk	Q_33	0.8869	<0.001	NO
34	Shapiro-Wilk	Q_34	0.873	<0.001	NO
35	Shapiro-Wilk	Q_35	0.8925	<0.001	NO
36	Shapiro-Wilk	Q_36	0.8923	<0.001	NO
37	Shapiro-Wilk	Q_37	0.7877	<0.001	NO
38	Shapiro-Wilk	Q_38	0.7175	<0.001	NO

	Test	Variable	Statistic	p-value	Normality
39	Shapiro-Wilk	Q_39	0.8531	<0.001	NO
40	Shapiro-Wilk	Q_40	0.8966	<0.001	NO
41	Shapiro-Wilk	Q_41	0.432	<0.001	NO
42	Shapiro-Wilk	Q_42	0.926	<0.001	NO
43	Shapiro-Wilk	Q_43	0.7859	<0.001	NO
44	Shapiro-Wilk	Q_44	0.7923	<0.001	NO
45	Shapiro-Wilk	Q_45	0.8726	<0.001	NO
46	Shapiro-Wilk	Q_46	0.8616	<0.001	NO
47	Shapiro-Wilk	Q_47	0.8514	<0.001	NO
48	Shapiro-Wilk	Q_48	0.9036	<0.001	NO
49	Shapiro-Wilk	Q_49	0.8636	<0.001	NO
50	Shapiro-Wilk	Q_50	0.8776	<0.001	NO
51	Shapiro-Wilk	Q_51	0.8288	<0.001	NO

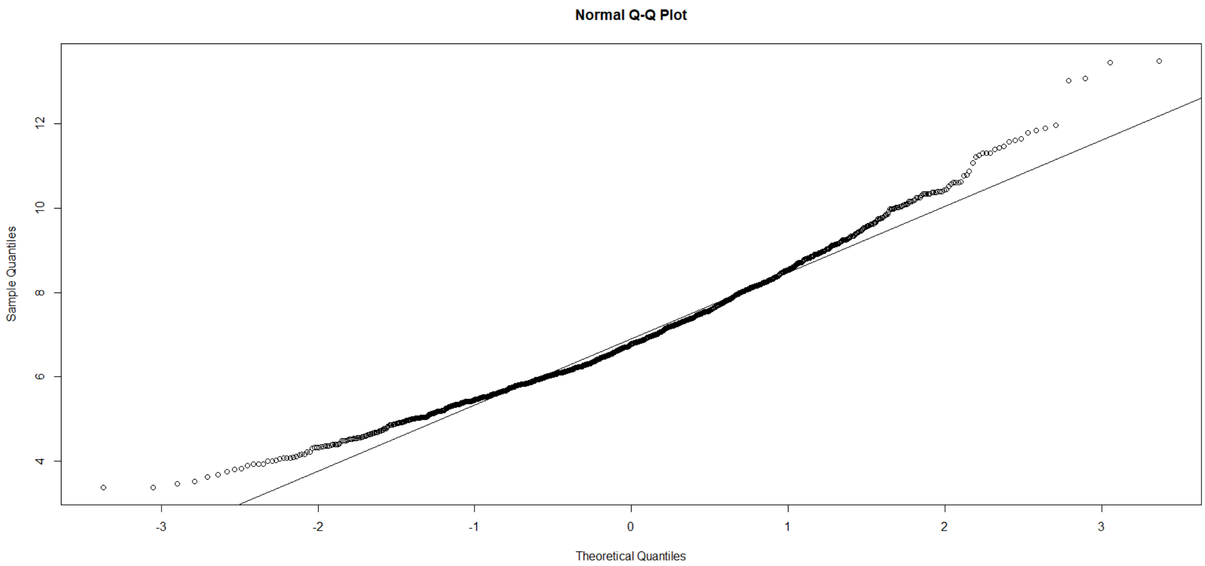

Figure 49: Student Likert normality QQ-plot

Table 74: Supervisor Likert skewness statistic

	Test	Variable	Statistic	p-value	Normality
1	Shapiro-Wilk	Q_01	0.8649	<0.001	NO
2	Shapiro-Wilk	Q_02	0.9402	<0.001	NO
3	Shapiro-Wilk	Q_03	0.9031	<0.001	NO
4	Shapiro-Wilk	Q_04	0.8523	<0.001	NO
5	Shapiro-Wilk	Q_05	0.9339	<0.001	NO
6	Shapiro-Wilk	Q_06	0.7652	<0.001	NO
7	Shapiro-Wilk	Q_07	0.9139	<0.001	NO
8	Shapiro-Wilk	Q_08	0.7966	<0.001	NO
9	Shapiro-Wilk	Q_09	0.936	<0.001	NO
10	Shapiro-Wilk	Q_10	0.93	<0.001	NO
11	Shapiro-Wilk	Q_11	0.8967	<0.001	NO
12	Shapiro-Wilk	Q_12	0.897	<0.001	NO
13	Shapiro-Wilk	Q_13	0.9345	<0.001	NO
14	Shapiro-Wilk	Q_14	0.88	<0.001	NO
15	Shapiro-Wilk	Q_15	0.908	<0.001	NO
16	Shapiro-Wilk	Q_16	0.9253	<0.001	NO
17	Shapiro-Wilk	Q_17	0.8498	<0.001	NO
18	Shapiro-Wilk	Q_18	0.9055	<0.001	NO
19	Shapiro-Wilk	Q_19	0.8705	<0.001	NO
20	Shapiro-Wilk	Q_20	0.8774	<0.001	NO
21	Shapiro-Wilk	Q_21	0.7152	<0.001	NO
22	Shapiro-Wilk	Q_22	0.9519	<0.001	NO
23	Shapiro-Wilk	Q_23	0.9404	<0.001	NO
24	Shapiro-Wilk	Q_24	0.9003	<0.001	NO
25	Shapiro-Wilk	Q_25	0.9352	<0.001	NO
26	Shapiro-Wilk	Q_26	0.9466	<0.001	NO
27	Shapiro-Wilk	Q_27	0.7602	<0.001	NO
28	Shapiro-Wilk	Q_28	0.8859	<0.001	NO
29	Shapiro-Wilk	Q_29	0.9142	<0.001	NO
30	Shapiro-Wilk	Q_30	0.8864	<0.001	NO
31	Shapiro-Wilk	Q_31	0.9203	<0.001	NO
32	Shapiro-Wilk	Q_32	0.8792	<0.001	NO
33	Shapiro-Wilk	Q_33	0.6549	<0.001	NO
34	Shapiro-Wilk	Q_34	0.9328	<0.001	NO
35	Shapiro-Wilk	Q_35	0.9238	<0.001	NO
36	Shapiro-Wilk	Q_36	0.8369	<0.001	NO
37	Shapiro-Wilk	Q_37	0.8513	<0.001	NO
38	Shapiro-Wilk	Q_38	0.8603	<0.001	NO
39	Shapiro-Wilk	Q_39	0.882	<0.001	NO
40	Shapiro-Wilk	Q_40	0.9369	<0.001	NO
41	Shapiro-Wilk	Q_41	0.6311	<0.001	NO
42	Shapiro-Wilk	Q_42	0.9445	<0.001	NO
43	Shapiro-Wilk	Q_43	0.9212	<0.001	NO
44	Shapiro-Wilk	Q_44	0.9212	<0.001	NO
45	Shapiro-Wilk	Q_45	0.9168	<0.001	NO

	Test	Variable	Statistic	p-value	Normality
46	Shapiro-Wilk	Q_46	0.8872	<0.001	NO
47	Shapiro-Wilk	Q_47	0.8916	<0.001	NO
48	Shapiro-Wilk	Q_48	0.9127	<0.001	NO
49	Shapiro-Wilk	Q_49	0.9341	<0.001	NO
50	Shapiro-Wilk	Q_50	0.9132	<0.001	NO
51	Shapiro-Wilk	Q_51	0.8496	<0.001	NO

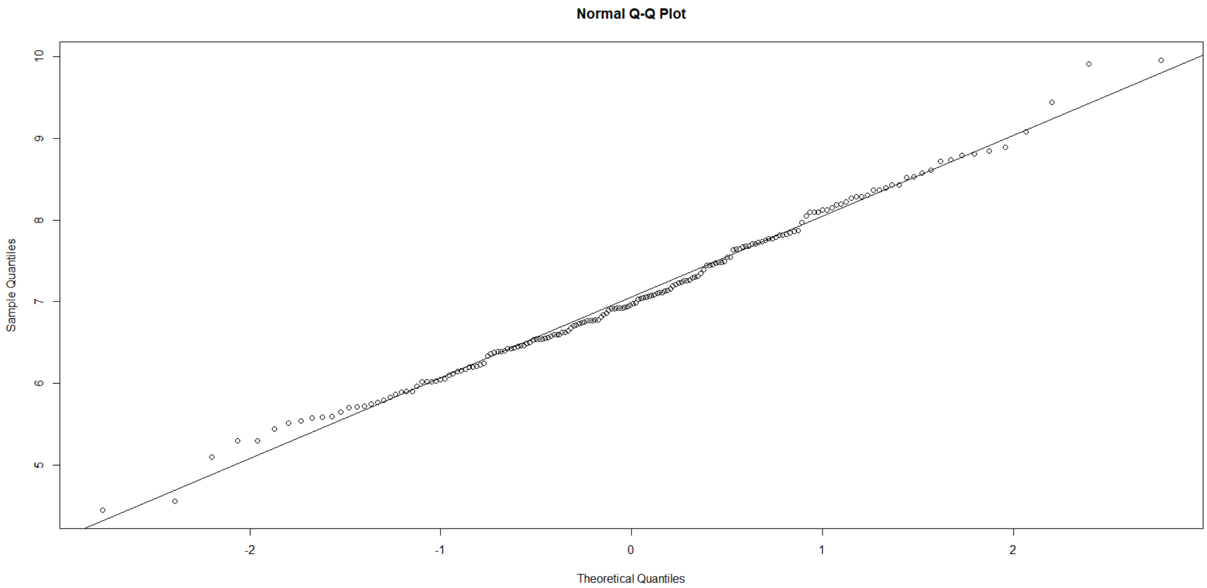

Figure 50: Supervisor Likert normality QQ-plot

Full confirmatory factor analysis model outputs

CFA Six-Factor Model

```
lavaan 0.6-7 ended normally after 36 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                        117

  Number of observations                          1323

Model Test User Model:

  Test statistic                              6319.449
  Degrees of freedom                              1209
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             18443.596
  Degrees of freedom                              1275
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.702
  Tucker-Lewis Index (TLI)                       0.686

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)            -124932.866
  Loglikelihood unrestricted model (H1)    -121770.751

  Akaike (AIC)                              250099.731
  Bayesian (BIC)                            250706.687
  Sample-size adjusted Bayesian (BIC)       250335.031

Root Mean Square Error of Approximation:

  RMSEA                                          0.057
  90 Percent confidence interval - lower         0.055
  90 Percent confidence interval - upper         0.058
  P-value RMSEA <= 0.05                          0.000
```

```
Standardized Root Mean Square Residual:

  SRMR                                           0.065

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  ST_AS =~
    Q_01              1.098    0.048   22.833    0.000    1.098    0.623
    Q_02              1.017    0.048   21.275    0.000    1.017    0.588
    Q_03              1.045    0.041   25.415    0.000    1.045    0.679
    Q_04             -0.186    0.060   -3.079    0.002   -0.186   -0.094
    Q_05              1.086    0.047   22.980    0.000    1.086    0.626
    Q_06              0.593    0.031   18.989    0.000    0.593    0.534
    Q_07             -0.104    0.063   -1.650    0.099   -0.104   -0.050
    Q_08              0.657    0.037   17.981    0.000    0.657    0.510
    Q_09             -0.017    0.057   -0.303    0.762   -0.017   -0.009
  ST_OR =~
    Q_10              0.640    0.057   11.168    0.000    0.640    0.314
    Q_11              0.750    0.053   14.235    0.000    0.750    0.394
    Q_12              0.897    0.037   23.945    0.000    0.897    0.619
    Q_13              1.007    0.044   23.132    0.000    1.007    0.602
    Q_14              0.847    0.044   19.057    0.000    0.847    0.512
    Q_15              0.937    0.042   22.500    0.000    0.937    0.589
    Q_16             -0.166    0.058   -2.871    0.004   -0.166   -0.083
    Q_17              1.053    0.039   27.170    0.000    1.053    0.684
    Q_18              0.573    0.041   13.847    0.000    0.573    0.384
    Q_19              0.867    0.041   21.361    0.000    0.867    0.564
    Q_20              0.099    0.046    2.136    0.033    0.099    0.062
    Q_21              0.670    0.048   14.067    0.000    0.670    0.390
    Q_22              0.327    0.050    6.533    0.000    0.327    0.187
    Q_23              0.347    0.055    6.274    0.000    0.347    0.180
  ST_SP =~
    Q_24              0.893    0.036   24.692    0.000    0.893    0.643
    Q_25              0.925    0.049   18.851    0.000    0.925    0.514
    Q_26              0.804    0.056   14.398    0.000    0.804    0.404
    Q_27              0.926    0.040   23.040    0.000    0.926    0.608
    Q_28              0.926    0.040   23.332    0.000    0.926    0.614
    Q_29              0.213    0.055    3.858    0.000    0.213    0.113
    Q_30              0.926    0.044   20.876    0.000    0.926    0.561
```

```
    Q_31              1.137    0.058   19.689    0.000    1.137    0.533
  SU_FI =~
    Q_32              0.789    0.042   18.993    0.000    0.789    0.587
    Q_33              1.202    0.065   18.445    0.000    1.202    0.566
  SU_MA =~
    Q_34              1.499    0.051   29.236    0.000    1.499    0.763
    Q_35              0.198    0.065    3.059    0.002    0.198    0.093
    Q_36              1.601    0.057   28.246    0.000    1.601    0.741
    Q_37              0.737    0.044   16.734    0.000    0.737    0.478
  SU_PC =~
    Q_38              0.428    0.030   14.340    0.000    0.428    0.406
    Q_39              0.730    0.048   15.253    0.000    0.730    0.429
    Q_40              0.588    0.054   10.861    0.000    0.588    0.313
    Q_41              0.352    0.022   15.679    0.000    0.352    0.440
    Q_42              0.481    0.052    9.258    0.000    0.481    0.269
    Q_43              0.268    0.059    4.580    0.000    0.268    0.135
    Q_44              0.971    0.042   23.003    0.000    0.971    0.611
    Q_45             -0.382    0.065   -5.921    0.000   -0.382   -0.174
    Q_46              0.786    0.051   15.501    0.000    0.786    0.435
    Q_47              0.939    0.038   24.662    0.000    0.939    0.646
    Q_48             -0.310    0.050   -6.163    0.000   -0.310   -0.181
    Q_49              0.837    0.047   17.897    0.000    0.837    0.494
    Q_50              1.095    0.049   22.361    0.000    1.095    0.597
    Q_51             -0.065    0.054   -1.196    0.232   -0.065   -0.035

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  ST_AS ~~
    ST_OR             0.772    0.019   39.706    0.000    0.772    0.772
    ST_SP             0.661    0.024   27.146    0.000    0.661    0.661
    SU_FI             0.490    0.040   12.264    0.000    0.490    0.490
    SU_MA             0.434    0.031   13.825    0.000    0.434    0.434
    SU_PC             0.624    0.026   24.440    0.000    0.624    0.624
  ST_OR ~~
    ST_SP             0.939    0.013   71.586    0.000    0.939    0.939
    SU_FI             0.750    0.034   21.780    0.000    0.750    0.750
    SU_MA             0.715    0.023   31.590    0.000    0.715    0.715
    SU_PC             0.889    0.015   59.349    0.000    0.889    0.889
  ST_SP ~~
    SU_FI             0.774    0.035   22.099    0.000    0.774    0.774
    SU_MA             0.743    0.023   32.765    0.000    0.743    0.743
    SU_PC             0.861    0.017   50.201    0.000    0.861    0.861
  SU_FI ~~
    SU_MA             0.925    0.034   27.332    0.000    0.925    0.925
    SU_PC             0.864    0.034   25.782    0.000    0.864    0.864
```

```
  SU_MA ~~
    SU_PC             0.706    0.024   29.576    0.000    0.706    0.706

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.900    0.087   21.955    0.000    1.900    0.612
   .Q_02              1.956    0.087   22.592    0.000    1.956    0.654
   .Q_03              1.276    0.062   20.631    0.000    1.276    0.539
   .Q_04              3.913    0.153   25.658    0.000    3.913    0.991
   .Q_05              1.827    0.083   21.889    0.000    1.827    0.608
   .Q_06              0.880    0.038   23.361    0.000    0.880    0.715
   .Q_07              4.242    0.165   25.695    0.000    4.242    0.997
   .Q_08              1.231    0.052   23.648    0.000    1.231    0.740
   .Q_09              3.539    0.138   25.709    0.000    3.539    1.000
   .Q_10              3.732    0.147   25.412    0.000    3.732    0.901
   .Q_11              3.051    0.121   25.207    0.000    3.051    0.844
   .Q_12              1.293    0.054   23.938    0.000    1.293    0.616
   .Q_13              1.782    0.074   24.097    0.000    1.782    0.637
   .Q_14              2.022    0.082   24.725    0.000    2.022    0.738
   .Q_15              1.654    0.068   24.212    0.000    1.654    0.653
   .Q_16              3.968    0.154   25.691    0.000    3.968    0.993
   .Q_17              1.263    0.055   23.145    0.000    1.263    0.533
   .Q_18              1.892    0.075   25.236    0.000    1.892    0.852
   .Q_19              1.611    0.066   24.401    0.000    1.611    0.682
   .Q_20              2.541    0.099   25.700    0.000    2.541    0.996
   .Q_21              2.502    0.099   25.220    0.000    2.502    0.848
   .Q_22              2.954    0.115   25.612    0.000    2.954    0.965
   .Q_23              3.598    0.140   25.620    0.000    3.598    0.968
   .Q_24              1.131    0.049   23.011    0.000    1.131    0.587
   .Q_25              2.382    0.098   24.386    0.000    2.382    0.736
   .Q_26              3.312    0.132   25.001    0.000    3.312    0.837
   .Q_27              1.459    0.062   23.491    0.000    1.459    0.630
   .Q_28              1.414    0.060   23.412    0.000    1.414    0.622
   .Q_29              3.521    0.137   25.664    0.000    3.521    0.987
   .Q_30              1.872    0.078   24.001    0.000    1.872    0.686
   .Q_31              3.250    0.134   24.236    0.000    3.250    0.715
   .Q_32              1.185    0.060   19.733    0.000    1.185    0.655
   .Q_33              3.069    0.149   20.584    0.000    3.069    0.680
   .Q_34              1.614    0.095   17.036    0.000    1.614    0.418
   .Q_35              4.487    0.175   25.660    0.000    4.487    0.991
   .Q_36              2.102    0.116   18.176    0.000    2.102    0.451
   .Q_37              1.832    0.076   23.978    0.000    1.832    0.771
   .Q_38              0.931    0.037   24.904    0.000    0.931    0.836
   .Q_39              2.365    0.095   24.785    0.000    2.365    0.816
   .Q_40              3.181    0.126   25.268    0.000    3.181    0.902
```

.Q_41	0.518	0.021	24.725	0.000	0.518	0.807
.Q_42	2.974	0.117	25.394	0.000	2.974	0.928
.Q_43	3.888	0.152	25.635	0.000	3.888	0.982
.Q_44	1.581	0.068	23.199	0.000	1.581	0.627
.Q_45	4.697	0.184	25.584	0.000	4.697	0.970
.Q_46	2.642	0.107	24.750	0.000	2.642	0.811
.Q_47	1.228	0.054	22.662	0.000	1.228	0.582
.Q_48	2.836	0.111	25.573	0.000	2.836	0.967
.Q_49	2.165	0.089	24.373	0.000	2.165	0.755
.Q_50	2.164	0.093	23.382	0.000	2.164	0.643
.Q_51	3.372	0.131	25.705	0.000	3.372	0.999
ST_AS	1.000				1.000	1.000
ST_OR	1.000				1.000	1.000
ST_SP	1.000				1.000	1.000
SU_FI	1.000				1.000	1.000
SU_MA	1.000				1.000	1.000
SU_PC	1.000				1.000	1.000

Modification Index

lhs	op	rhs	mi	epc
Q_09	~~	Q_22	168.9	1.157
Q_40	~~	Q_42	156.9	1.075
Q_09	~~	Q_16	139	1.215
Q_04	~~	Q_09	135.8	1.193
Q_38	~~	Q_41	129	0.2251
Q_20	~~	Q_22	123.3	0.8383
Q_12	~~	Q_28	117.5	0.4371
Q_09	~~	Q_29	116.8	1.05
ST_SP	=~	Q_37	109	0.837
Q_16	~~	Q_48	107.5	0.959
Q_04	~~	Q_22	90.12	0.8896
Q_25	~~	Q_31	87.81	0.764
ST_OR	=~	Q_37	83.54	0.6555
Q_24	~~	Q_27	82.45	0.3647
ST_AS	=~	Q_40	79.64	0.7242
SU_PC	=~	Q_37	78.04	0.6848
Q_16	~~	Q_51	73.07	0.86
Q_22	~~	Q_29	72.73	0.7581
SU_PC	=~	Q_12	71.12	1.005
Q_09	~~	Q_48	71.01	0.7357
Q_09	~~	Q_20	68.39	0.682
Q_34	~~	Q_36	67.9	1.113

Q_22	~~	Q_35	64.22	0.8041
Q_29	~~	Q_35	63.99	0.8755
Q_16	~~	Q_22	63.79	0.7535
SU_FI	=~	Q_12	58.91	0.5567
Q_29	~~	Q_48	57.29	0.6596
Q_09	~~	Q_35	56.68	0.8255
ST_OR	=~	Q_40	56.66	1.284
Q_42	~~	Q_51	56.31	0.6574
Q_06	~~	Q_41	56.16	0.147
Q_09	~~	Q_51	55.86	0.7099
Q_22	~~	Q_48	55.17	0.5935
Q_16	~~	Q_29	54.98	0.7629
Q_22	~~	Q_42	54.59	0.6064
Q_04	~~	Q_16	54.52	0.8009
Q_19	~~	Q_30	54.28	0.3731
Q_09	~~	Q_42	53.96	0.6588
Q_16	~~	Q_23	53.87	0.7641
SU_PC	=~	Q_02	51.49	-0.4883
Q_45	~~	Q_51	51.34	0.786
Q_16	~~	Q_42	51.18	0.6796
Q_35	~~	Q_48	49.38	0.6913

Table: Largest MI values

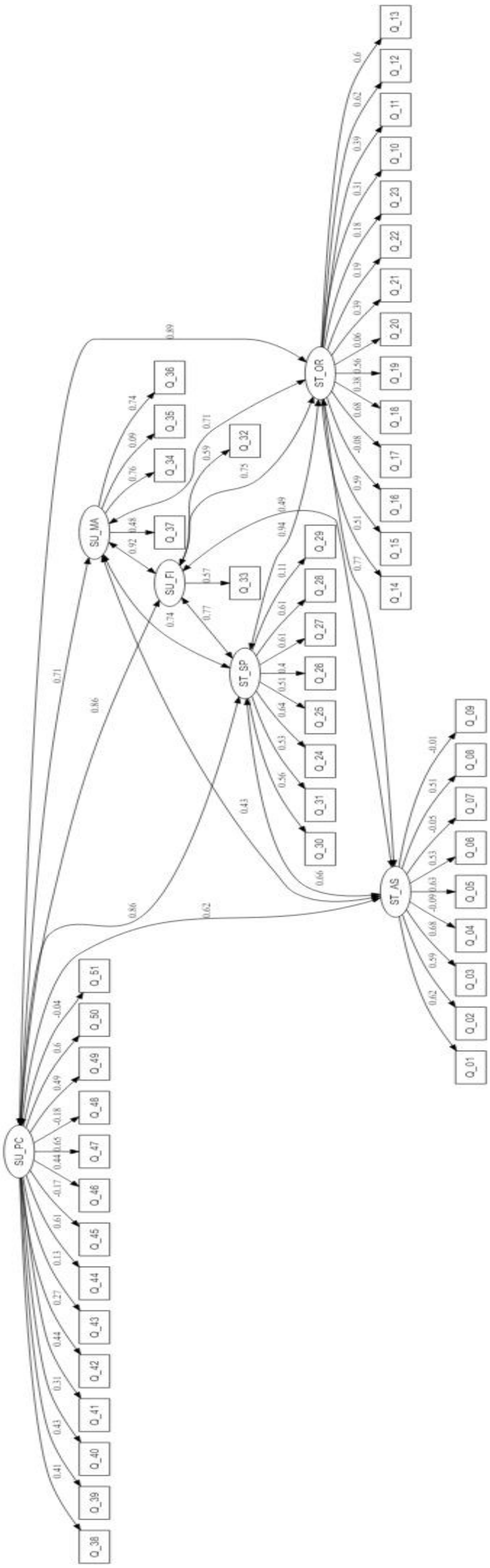

Figure 51: CFA Six-Factor Model Lavaan Plot

CFA Two-Factor Model

```
lavaan 0.6-7 ended normally after 28 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                        103

  Number of observations                          1323

Model Test User Model:

  Test statistic                              7135.825
  Degrees of freedom                              1223
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             18443.596
  Degrees of freedom                              1275
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.656
  Tucker-Lewis Index (TLI)                       0.641

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)            -125341.362
  Loglikelihood unrestricted model (H1)    -121770.751

  Akaike (AIC)                              250888.725
  Bayesian (BIC)                            251423.053
  Sample-size adjusted Bayesian (BIC)       251095.869

Root Mean Square Error of Approximation:

  RMSEA                                          0.060
  90 Percent confidence interval - lower         0.059
  90 Percent confidence interval - upper         0.062
  P-value RMSEA <= 0.05                          0.000

Standardized Root Mean Square Residual:

  SRMR                                           0.066
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              0.905    0.047   19.243    0.000    0.905    0.513
    Q_02              0.709    0.047   14.936    0.000    0.709    0.410
    Q_03              0.861    0.040   21.310    0.000    0.861    0.560
    Q_04             -0.262    0.057   -4.604    0.000   -0.262   -0.132
    Q_05              0.838    0.047   17.940    0.000    0.838    0.483
    Q_06              0.518    0.030   17.270    0.000    0.518    0.467
    Q_07              0.088    0.059    1.479    0.139    0.088    0.043
    Q_08              0.551    0.035   15.614    0.000    0.551    0.427
    Q_09             -0.070    0.054   -1.298    0.194   -0.070   -0.037
    Q_10              0.633    0.057   11.106    0.000    0.633    0.311
    Q_11              0.749    0.052   14.292    0.000    0.749    0.394
    Q_12              0.883    0.037   23.648    0.000    0.883    0.610
    Q_13              1.002    0.043   23.134    0.000    1.002    0.599
    Q_14              0.838    0.044   18.928    0.000    0.838    0.506
    Q_15              0.933    0.041   22.551    0.000    0.933    0.587
    Q_16             -0.168    0.057   -2.924    0.003   -0.168   -0.084
    Q_17              1.043    0.039   27.036    0.000    1.043    0.677
    Q_18              0.571    0.041   13.860    0.000    0.571    0.383
    Q_19              0.871    0.040   21.633    0.000    0.871    0.567
    Q_20              0.100    0.046    2.183    0.029    0.100    0.063
    Q_21              0.656    0.047   13.817    0.000    0.656    0.382
    Q_22              0.318    0.050    6.375    0.000    0.318    0.182
    Q_23              0.337    0.055    6.121    0.000    0.337    0.175
    Q_24              0.855    0.036   23.951    0.000    0.855    0.616
    Q_25              0.882    0.048   18.243    0.000    0.882    0.490
    Q_26              0.747    0.055   13.576    0.000    0.747    0.376
    Q_27              0.887    0.040   22.379    0.000    0.887    0.583
    Q_28              0.898    0.039   22.980    0.000    0.898    0.596
    Q_29              0.204    0.054    3.771    0.000    0.204    0.108
    Q_30              0.920    0.043   21.179    0.000    0.920    0.557
    Q_31              1.067    0.057   18.680    0.000    1.067    0.500
  Support =~
    Q_32              0.772    0.036   21.595    0.000    0.772    0.574
    Q_33              1.060    0.058   18.314    0.000    1.060    0.499
    Q_34              1.218    0.051   23.751    0.000    1.218    0.620
    Q_35              0.143    0.062    2.302    0.021    0.143    0.067
```

```
    Q_36              1.299    0.057   22.857    0.000    1.299    0.601
    Q_37              0.774    0.042   18.431    0.000    0.774    0.502
    Q_38              0.398    0.030   13.417    0.000    0.398    0.377
    Q_39              0.711    0.047   14.995    0.000    0.711    0.418
    Q_40              0.594    0.053   11.108    0.000    0.594    0.316
    Q_41              0.327    0.022   14.640    0.000    0.327    0.409
    Q_42              0.476    0.051    9.265    0.000    0.476    0.266
    Q_43              0.237    0.058    4.087    0.000    0.237    0.119
    Q_44              0.933    0.042   22.216    0.000    0.933    0.587
    Q_45             -0.372    0.064   -5.824    0.000   -0.372   -0.169
    Q_46              0.757    0.050   15.062    0.000    0.757    0.420
    Q_47              0.901    0.038   23.762    0.000    0.901    0.620
    Q_48             -0.319    0.050   -6.433    0.000   -0.319   -0.186
    Q_49              0.823    0.046   17.768    0.000    0.823    0.486
    Q_50              1.110    0.048   23.055    0.000    1.110    0.605
    Q_51             -0.049    0.054   -0.904    0.366   -0.049   -0.026

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure ~~
    Support           0.870    0.011   76.707    0.000    0.870    0.870

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              2.288    0.092   24.843    0.000    2.288    0.736
   .Q_02              2.487    0.099   25.220    0.000    2.487    0.832
   .Q_03              1.625    0.066   24.604    0.000    1.625    0.687
   .Q_04              3.879    0.151   25.667    0.000    3.879    0.983
   .Q_05              2.305    0.092   24.972    0.000    2.305    0.767
   .Q_06              0.963    0.038   25.034    0.000    0.963    0.782
   .Q_07              4.245    0.165   25.706    0.000    4.245    0.998
   .Q_08              1.360    0.054   25.170    0.000    1.360    0.818
   .Q_09              3.535    0.138   25.707    0.000    3.535    0.999
   .Q_10              3.740    0.147   25.450    0.000    3.740    0.903
   .Q_11              3.052    0.121   25.265    0.000    3.052    0.845
   .Q_12              1.318    0.054   24.276    0.000    1.318    0.628
   .Q_13              1.793    0.074   24.354    0.000    1.793    0.641
   .Q_14              2.038    0.082   24.875    0.000    2.038    0.744
   .Q_15              1.660    0.068   24.438    0.000    1.660    0.656
   .Q_16              3.968    0.154   25.693    0.000    3.968    0.993
   .Q_17              1.285    0.054   23.657    0.000    1.285    0.542
   .Q_18              1.895    0.075   25.294    0.000    1.895    0.853
   .Q_19              1.603    0.065   24.562    0.000    1.603    0.679
   .Q_20              2.541    0.099   25.700    0.000    2.541    0.996
   .Q_21              2.521    0.100   25.297    0.000    2.521    0.854
```

.Q_22	2.960	0.115	25.627	0.000	2.960	0.967
.Q_23	3.605	0.141	25.634	0.000	3.605	0.969
.Q_24	1.197	0.049	24.228	0.000	1.197	0.621
.Q_25	2.459	0.099	24.944	0.000	2.459	0.760
.Q_26	3.400	0.134	25.312	0.000	3.400	0.859
.Q_27	1.529	0.062	24.462	0.000	1.529	0.660
.Q_28	1.465	0.060	24.376	0.000	1.465	0.645
.Q_29	3.525	0.137	25.681	0.000	3.525	0.988
.Q_30	1.883	0.076	24.620	0.000	1.883	0.690
.Q_31	3.405	0.137	24.901	0.000	3.405	0.750
.Q_32	1.212	0.050	24.035	0.000	1.212	0.671
.Q_33	3.390	0.138	24.581	0.000	3.390	0.751
.Q_34	2.377	0.101	23.576	0.000	2.377	0.616
.Q_35	4.505	0.175	25.695	0.000	4.505	0.995
.Q_36	2.979	0.125	23.778	0.000	2.979	0.639
.Q_37	1.778	0.072	24.564	0.000	1.778	0.748
.Q_38	0.955	0.038	25.146	0.000	0.955	0.858
.Q_39	2.392	0.096	24.991	0.000	2.392	0.825
.Q_40	3.173	0.125	25.333	0.000	3.173	0.900
.Q_41	0.534	0.021	25.028	0.000	0.534	0.833
.Q_42	2.979	0.117	25.452	0.000	2.979	0.929
.Q_43	3.903	0.152	25.661	0.000	3.903	0.986
.Q_44	1.653	0.069	23.912	0.000	1.653	0.655
.Q_45	4.705	0.184	25.610	0.000	4.705	0.971
.Q_46	2.686	0.108	24.984	0.000	2.686	0.824
.Q_47	1.298	0.055	23.574	0.000	1.298	0.615
.Q_48	2.830	0.111	25.588	0.000	2.830	0.965
.Q_49	2.189	0.089	24.657	0.000	2.189	0.764
.Q_50	2.130	0.090	23.734	0.000	2.130	0.633
.Q_51	3.374	0.131	25.708	0.000	3.374	0.999
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000

Modification index

lhs	op	rhs	mi	epc
Q_34	~~	Q_36	214.3	1.177
Q_09	~~	Q_22	169.6	1.16
Q_40	~~	Q_42	156.2	1.07
Q_38	~~	Q_41	143	0.2409
Q_09	~~	Q_16	138.8	1.214
Q_04	~~	Q_09	133.6	1.178

Q_02	~~	Q_05	129.8	0.769
Q_20	~~	Q_22	123.1	0.8382
Q_02	~~	Q_03	117.9	0.6202
Q_09	~~	Q_29	116	1.046
Q_12	~~	Q_28	115.4	0.4359
Q_16	~~	Q_48	107.7	0.9584
Q_25	~~	Q_31	103.4	0.8358
Q_24	~~	Q_27	99.56	0.3937
Q_33	~~	Q_36	94.53	0.9087
Q_04	~~	Q_22	91.45	0.893
Support	=~	Q_12	78.69	0.8663
Q_36	~~	Q_41	75.32	-0.3183
Support	=~	Q_02	74.97	-1.125
Q_22	~~	Q_29	73.06	0.7607
Q_16	~~	Q_51	73.05	0.86
Q_09	~~	Q_48	71.15	0.7351
Q_09	~~	Q_20	68.59	0.6826
Q_22	~~	Q_35	64.57	0.8082
Q_16	~~	Q_22	63.49	0.7522
Q_29	~~	Q_35	63.27	0.8721
Q_02	~~	Q_23	61.78	-0.6542
Q_06	~~	Q_41	57.16	0.1528
Q_29	~~	Q_48	56.7	0.6555
Q_09	~~	Q_35	56.32	0.8236
Q_09	~~	Q_51	55.93	0.7101
Q_22	~~	Q_48	55.53	0.5951
Q_04	~~	Q_16	54.87	0.7999
Q_16	~~	Q_29	54.83	0.762
Q_01	~~	Q_05	54.68	0.4826
Q_42	~~	Q_51	54.66	0.6476
Q_22	~~	Q_42	53.8	0.6024
Q_09	~~	Q_42	53.71	0.6568
Q_16	~~	Q_23	53.63	0.7628
Q_45	~~	Q_51	52.06	0.7919
Q_02	~~	Q_40	51.63	0.5637
Q_16	~~	Q_42	51.11	0.6789
Q_35	~~	Q_48	49.41	0.6919
Q_03	~~	Q_05	49.26	0.3882

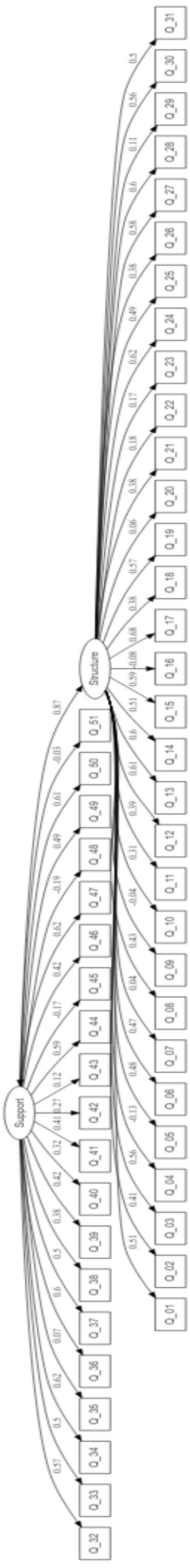

Figure 52: CFA Two-Factor Model Lavaan Plot

CFA Six-Factor Modified Model

```
lavaan 0.6-7 ended normally after 35 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         67

  Number of observations                          1323

Model Test User Model:

  Test statistic                               956.302
  Degrees of freedom                               258
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                             10336.291
  Degrees of freedom                               300
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.930
  Tucker-Lewis Index (TLI)                       0.919

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -58466.872
  Loglikelihood unrestricted model (H1)     -57988.359

  Akaike (AIC)                              117067.743
  Bayesian (BIC)                            117415.316
  Sample-size adjusted Bayesian (BIC)       117202.488

Root Mean Square Error of Approximation:

  RMSEA                                          0.045
  90 Percent confidence interval - lower         0.042
  90 Percent confidence interval - upper         0.048
  P-value RMSEA <= 0.05                          0.995

Standardized Root Mean Square Residual:

  SRMR                                           0.039
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  ST_AS =~
    Q_01              1.096    0.048   22.753    0.000    1.096    0.622
    Q_02              1.032    0.048   21.624    0.000    1.032    0.597
    Q_03              1.044    0.041   25.361    0.000    1.044    0.679
    Q_05              1.095    0.047   23.189    0.000    1.095    0.632
    Q_06              0.586    0.031   18.724    0.000    0.586    0.528
    Q_08              0.649    0.037   17.700    0.000    0.649    0.503
  ST_OR =~
    Q_13              1.048    0.044   23.818    0.000    1.048    0.627
    Q_14              0.864    0.045   19.141    0.000    0.864    0.522
    Q_15              0.987    0.042   23.513    0.000    0.987    0.620
    Q_17              1.068    0.039   27.059    0.000    1.068    0.693
    Q_19              0.887    0.041   21.531    0.000    0.887    0.577
  ST_SP =~
    Q_24              0.852    0.037   23.052    0.000    0.852    0.614
    Q_25              0.881    0.050   17.753    0.000    0.881    0.490
    Q_27              0.875    0.041   21.298    0.000    0.875    0.575
    Q_28              0.901    0.040   22.444    0.000    0.901    0.598
    Q_30              0.950    0.044   21.427    0.000    0.950    0.575
    Q_31              1.100    0.058   18.855    0.000    1.100    0.516
  SU_FI =~
    Q_32              0.774    0.042   18.638    0.000    0.774    0.576
    Q_33              1.226    0.066   18.679    0.000    1.226    0.577
  SU_MA =~
    Q_34              1.533    0.052   29.410    0.000    1.533    0.780
    Q_36              1.668    0.057   29.080    0.000    1.668    0.772
  SU_PC =~
    Q_44              0.984    0.043   22.624    0.000    0.984    0.619
    Q_47              0.919    0.040   23.226    0.000    0.919    0.633
    Q_49              0.840    0.048   17.466    0.000    0.840    0.496
    Q_50              1.150    0.050   22.962    0.000    1.150    0.627

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_25 ~~
   .Q_31              0.754    0.087    8.657    0.000    0.754    0.263
```

```
 .Q_24 ~~
   .Q_27             0.363    0.044    8.231    0.000    0.363    0.266
  ST_AS ~~
    ST_OR            0.777    0.021   37.473    0.000    0.777    0.777
    ST_SP            0.689    0.025   27.344    0.000    0.689    0.689
    SU_FI            0.486    0.040   12.145    0.000    0.486    0.486
    SU_MA            0.394    0.032   12.293    0.000    0.394    0.394
    SU_PC            0.559    0.030   18.824    0.000    0.559    0.559
  ST_OR ~~
    ST_SP            0.963    0.016   58.507    0.000    0.963    0.963
    SU_FI            0.617    0.038   16.085    0.000    0.617    0.617
    SU_MA            0.612    0.027   22.515    0.000    0.612    0.612
    SU_PC            0.795    0.023   34.835    0.000    0.795    0.795
  ST_SP ~~
    SU_FI            0.782    0.037   21.222    0.000    0.782    0.782
    SU_MA            0.688    0.026   26.310    0.000    0.688    0.688
    SU_PC            0.875    0.022   40.331    0.000    0.875    0.875
  SU_FI ~~
    SU_MA            0.898    0.034   26.407    0.000    0.898    0.898
    SU_PC            0.877    0.036   24.380    0.000    0.877    0.877
  SU_MA ~~
    SU_PC            0.700    0.026   26.559    0.000    0.700    0.700

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01             1.905    0.087   21.932    0.000    1.905    0.613
   .Q_02             1.925    0.086   22.408    0.000    1.925    0.644
   .Q_03             1.277    0.062   20.581    0.000    1.277    0.539
   .Q_05             1.807    0.083   21.733    0.000    1.807    0.601
   .Q_06             0.888    0.038   23.405    0.000    0.888    0.721
   .Q_08             1.242    0.052   23.694    0.000    1.242    0.747
   .Q_13             1.698    0.073   23.103    0.000    1.698    0.607
   .Q_14             1.993    0.082   24.250    0.000    1.993    0.727
   .Q_15             1.558    0.067   23.197    0.000    1.558    0.615
   .Q_17             1.232    0.056   21.840    0.000    1.232    0.519
   .Q_19             1.576    0.066   23.737    0.000    1.576    0.667
   .Q_24             1.202    0.052   23.061    0.000    1.202    0.623
   .Q_25             2.461    0.101   24.461    0.000    2.461    0.760
   .Q_27             1.550    0.066   23.570    0.000    1.550    0.669
   .Q_28             1.459    0.062   23.438    0.000    1.459    0.642
   .Q_30             1.827    0.077   23.729    0.000    1.827    0.669
   .Q_31             3.332    0.137   24.263    0.000    3.332    0.734
   .Q_32             1.209    0.060   20.130    0.000    1.209    0.669
   .Q_33             3.011    0.150   20.065    0.000    3.011    0.667
   .Q_34             1.511    0.100   15.184    0.000    1.511    0.391
```

.Q_36	1.884	0.120	15.705	0.000	1.884	0.404
.Q_44	1.556	0.071	21.975	0.000	1.556	0.616
.Q_47	1.264	0.058	21.667	0.000	1.264	0.599
.Q_49	2.161	0.091	23.831	0.000	2.161	0.754
.Q_50	2.040	0.094	21.805	0.000	2.040	0.607
ST_AS	1.000				1.000	1.000
ST_OR	1.000				1.000	1.000
ST_SP	1.000				1.000	1.000
SU_FI	1.000				1.000	1.000
SU_MA	1.000				1.000	1.000
SU_PC	1.000				1.000	1.000

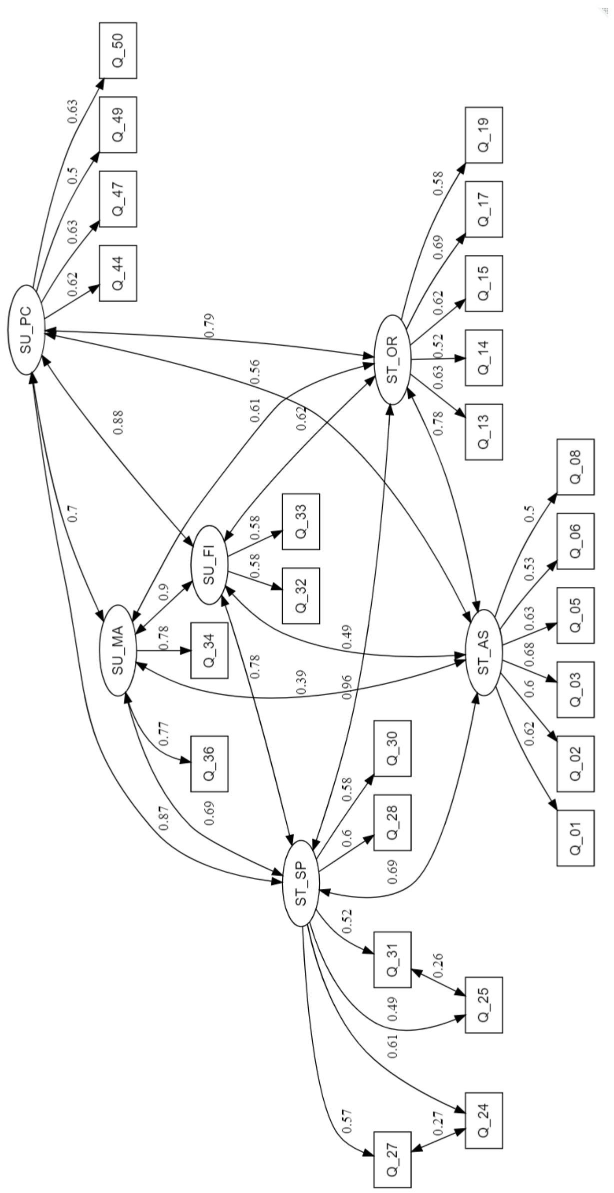

Figure 53: CFA Six-Factor Modified Model Lavaan Plot

CFA Two-Factor Modified Model

```
lavaan 0.6-7 ended normally after 31 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         52

  Number of observations                          1323

Model Test User Model:

  Test statistic                               959.530
  Degrees of freedom                               248
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              9272.511
  Degrees of freedom                               276
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.921
  Tucker-Lewis Index (TLI)                       0.912

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -55982.040
  Loglikelihood unrestricted model (H1)     -55501.912

  Akaike (AIC)                              112068.080
  Bayesian (BIC)                            112337.838
  Sample-size adjusted Bayesian (BIC)       112172.658

Root Mean Square Error of Approximation:

  RMSEA                                          0.047
  90 Percent confidence interval - lower         0.043
  90 Percent confidence interval - upper         0.050
  P-value RMSEA <= 0.05                          0.964

Standardized Root Mean Square Residual:

  SRMR                                           0.038
```

```
Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_03              0.829    0.041   20.020    0.000    0.829    0.539
    Q_06              0.503    0.031   16.419    0.000    0.503    0.453
    Q_08              0.519    0.036   14.387    0.000    0.519    0.402
    Q_13              0.985    0.044   22.305    0.000    0.985    0.589
    Q_14              0.856    0.045   19.094    0.000    0.856    0.517
    Q_15              0.949    0.042   22.645    0.000    0.949    0.597
    Q_17              1.075    0.039   27.676    0.000    1.075    0.698
    Q_19              0.888    0.041   21.771    0.000    0.888    0.578
    Q_24              0.856    0.036   23.540    0.000    0.856    0.617
    Q_25              0.859    0.049   17.375    0.000    0.859    0.477
    Q_27              0.877    0.041   21.654    0.000    0.877    0.577
    Q_28              0.893    0.040   22.464    0.000    0.893    0.593
    Q_30              0.955    0.044   21.797    0.000    0.955    0.578
    Q_31              1.059    0.058   18.210    0.000    1.059    0.497
  Support =~
    Q_32              0.759    0.037   20.799    0.000    0.759    0.565
    Q_34              1.147    0.053   21.585    0.000    1.147    0.584
    Q_36              1.196    0.059   20.243    0.000    1.196    0.554
    Q_37              0.790    0.043   18.545    0.000    0.790    0.512
    Q_39              0.695    0.048   14.356    0.000    0.695    0.408
    Q_44              0.959    0.043   22.556    0.000    0.959    0.604
    Q_46              0.771    0.051   15.098    0.000    0.771    0.427
    Q_47              0.923    0.038   24.022    0.000    0.923    0.635
    Q_49              0.836    0.047   17.764    0.000    0.836    0.494
    Q_50              1.129    0.049   23.108    0.000    1.129    0.616

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_25 ~~
   .Q_31              0.814    0.088    9.264    0.000    0.814    0.278
 .Q_34 ~~
   .Q_36              1.185    0.095   12.437    0.000    1.185    0.413
 .Q_24 ~~
   .Q_27              0.357    0.043    8.401    0.000    0.357    0.263
  Structure ~~
```

Support	0.854	0.014	61.259	0.000	0.854	0.854

Variances:

	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std.all
.Q_03	1.681	0.069	24.322	0.000	1.681	0.710
.Q_06	0.978	0.039	24.833	0.000	0.978	0.795
.Q_08	1.394	0.056	25.055	0.000	1.394	0.838
.Q_13	1.825	0.076	23.901	0.000	1.825	0.653
.Q_14	2.007	0.082	24.469	0.000	2.007	0.732
.Q_15	1.630	0.068	23.831	0.000	1.630	0.644
.Q_17	1.217	0.054	22.476	0.000	1.217	0.513
.Q_19	1.574	0.066	24.008	0.000	1.574	0.666
.Q_24	1.195	0.051	23.547	0.000	1.195	0.620
.Q_25	2.500	0.101	24.683	0.000	2.500	0.772
.Q_27	1.546	0.065	23.927	0.000	1.546	0.668
.Q_28	1.473	0.062	23.869	0.000	1.473	0.649
.Q_30	1.817	0.076	24.003	0.000	1.817	0.666
.Q_31	3.420	0.139	24.572	0.000	3.420	0.753
.Q_32	1.231	0.052	23.613	0.000	1.231	0.681
.Q_34	2.546	0.109	23.327	0.000	2.546	0.659
.Q_36	3.234	0.137	23.646	0.000	3.234	0.693
.Q_37	1.752	0.073	24.120	0.000	1.752	0.737
.Q_39	2.415	0.097	24.821	0.000	2.415	0.833
.Q_44	1.603	0.069	23.136	0.000	1.603	0.635
.Q_46	2.665	0.108	24.716	0.000	2.665	0.817
.Q_47	1.258	0.055	22.671	0.000	1.258	0.596
.Q_49	2.168	0.089	24.272	0.000	2.168	0.756
.Q_50	2.088	0.091	22.969	0.000	2.088	0.621
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000

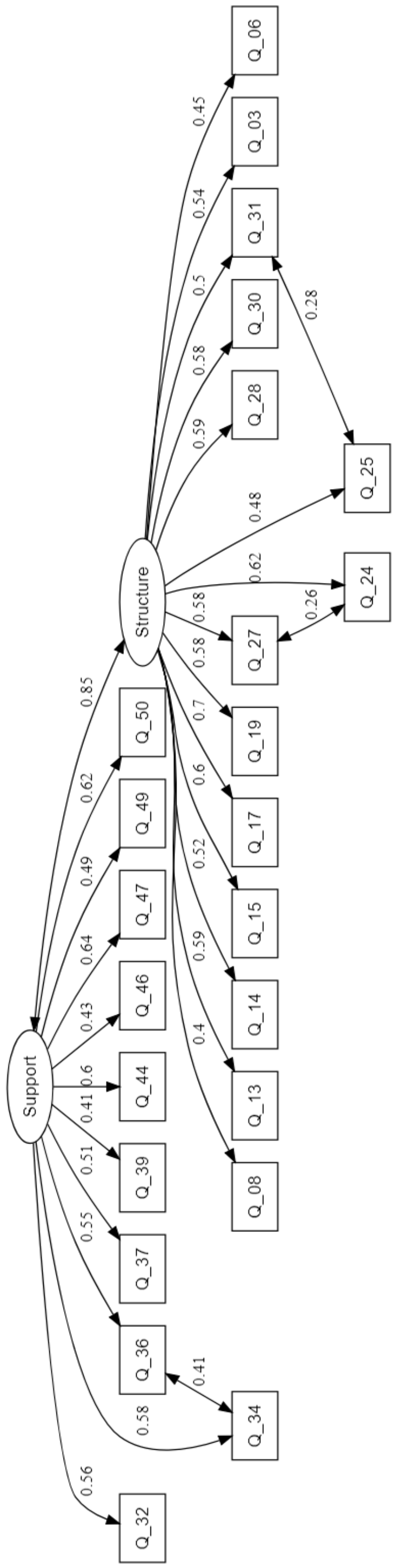

Figure 54: CFA Two-Factor Modified Model Lavaan Plot

Full exploratory factor analysis model outputs

EFA Two-Factor Orthogonal Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA2F, nfactors = 2, rotate = "varimax", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1  MR2   h2   u2 com
Q_34   16  0.67 0.09 0.46 0.54 1.0
Q_36   17  0.64 0.10 0.42 0.58 1.0
Q_44   20  0.61 0.19 0.41 0.59 1.2
Q_12    7  0.61 0.26 0.44 0.56 1.3
Q_50   23  0.58 0.24 0.40 0.60 1.3
Q_33   15  0.57 0.06 0.32 0.68 1.0
Q_32   14  0.56 0.20 0.35 0.65 1.3
Q_28   12  0.54 0.30 0.38 0.62 1.6
Q_49   22  0.50 0.09 0.25 0.75 1.1
Q_47   21  0.49 0.31 0.34 0.66 1.7
Q_24   10  0.46 0.36 0.34 0.66 1.9
Q_39   19  0.45 0.06 0.20 0.80 1.0
Q_27   11  0.44 0.38 0.34 0.66 2.0
Q_37   18  0.42 0.28 0.26 0.74 1.7
Q_31   13  0.42 0.23 0.23 0.77 1.6
Q_05    4  0.08 0.63 0.40 0.60 1.0
Q_02    2 -0.03 0.62 0.38 0.62 1.0
Q_01    1  0.22 0.59 0.39 0.61 1.3
Q_03    3  0.26 0.57 0.40 0.60 1.4
Q_15    9  0.31 0.52 0.37 0.63 1.6
Q_08    6  0.08 0.50 0.26 0.74 1.1
Q_06    5  0.28 0.48 0.31 0.69 1.6
Q_13    8  0.34 0.45 0.32 0.68 1.9

                       MR1  MR2
SS loadings           4.75 3.24
Proportion Var        0.21 0.14
Cumulative Var        0.21 0.35
Proportion Explained  0.59 0.41
Cumulative Proportion 0.59 1.00

Mean item complexity =  1.4
Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are  253  and the objective function was
7.45 with Chi Square of  4360.89
The degrees of freedom for the model are 208  and the objective function was  1.14
```

```
The root mean square of the residuals (RMSR) is  0.05
The df corrected root mean square of the residuals is  0.05

The harmonic number of observations is  595 with the empirical chi square  621.64
with prob <  8.3e-43
The total number of observations was  595  with Likelihood Chi Square =  667.24  with
prob <  1.5e-49

Tucker Lewis Index of factoring reliability =  0.864
RMSEA index =  0.061  and the 90 % confidence intervals are  0.056 0.066
BIC =  -661.58
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                   MR1  MR2
Correlation of (regression) scores with factors   0.92 0.88
Multiple R square of scores with factors          0.84 0.77
Minimum correlation of possible factor scores     0.68 0.55

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.04543977
number of absolute residuals > 0.05 =  62
Proportion of absolute residuals > 0.05 =  0.2450593
```

EFA Two-Factor Orthogonal Model CFA

```
lavaan 0.6-7 ended normally after 25 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         48

  Number of observations                           728

Model Test User Model:

  Test statistic                               623.213
  Degrees of freedom                               205
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              4872.067
  Degrees of freedom                               231
  P-value                                        0.000
```

```
User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.910
  Tucker-Lewis Index (TLI)                       0.898

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -28142.828
  Loglikelihood unrestricted model (H1)     -27830.793

  Akaike (AIC)                               56381.657
  Bayesian (BIC)                             56601.991
  Sample-size adjusted Bayesian (BIC)        56449.576

Root Mean Square Error of Approximation:

  RMSEA                                          0.053
  90 Percent confidence interval - lower         0.048
  90 Percent confidence interval - upper         0.058
  P-value RMSEA <= 0.05                          0.148

Standardized Root Mean Square Residual:

  SRMR                                           0.050

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.066    0.064   16.759    0.000    1.066    0.612
    Q_02              0.995    0.062   16.012    0.000    0.995    0.590
    Q_03              1.016    0.056   18.124    0.000    1.016    0.652
    Q_05              1.070    0.063   17.002    0.000    1.070    0.619
    Q_06              0.556    0.042   13.171    0.000    0.556    0.500
    Q_08              0.602    0.047   12.708    0.000    0.602    0.484
    Q_13              1.073    0.060   17.996    0.000    1.073    0.648
    Q_15              0.866    0.059   14.597    0.000    0.866    0.546
  Support =~
    Q_12              0.884    0.050   17.779    0.000    0.884    0.632
    Q_24              0.816    0.049   16.604    0.000    0.816    0.598
```

```
    Q_27              0.827    0.056   14.789    0.000    0.827    0.544
    Q_28              0.877    0.054   16.239    0.000    0.877    0.588
    Q_31              1.016    0.079   12.922    0.000    1.016    0.483
    Q_32              0.753    0.048   15.656    0.000    0.753    0.569
    Q_33              1.004    0.079   12.687    0.000    1.004    0.475
    Q_34              1.101    0.069   15.965    0.000    1.101    0.579
    Q_36              1.239    0.078   15.963    0.000    1.239    0.579
    Q_37              0.779    0.056   13.832    0.000    0.779    0.512
    Q_44              0.894    0.058   15.366    0.000    0.894    0.560
    Q_47              0.863    0.051   16.776    0.000    0.863    0.602
    Q_49              0.805    0.062   13.036    0.000    0.805    0.486
    Q_50              1.130    0.066   17.077    0.000    1.130    0.611

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_34 ~~
   .Q_36              1.020    0.119    8.574    0.000    1.020    0.377
 .Q_12 ~~
   .Q_28              0.401    0.057    6.975    0.000    0.401    0.307
 .Q_24 ~~
   .Q_27              0.407    0.060    6.826    0.000    0.407    0.292
  Structure ~~
    Support           0.668    0.029   23.351    0.000    0.668    0.668

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.895    0.113   16.711    0.000    1.895    0.625
   .Q_02              1.858    0.109   16.972    0.000    1.858    0.652
   .Q_03              1.397    0.086   16.160    0.000    1.397    0.575
   .Q_05              1.842    0.111   16.620    0.000    1.842    0.616
   .Q_06              0.927    0.052   17.763    0.000    0.927    0.750
   .Q_08              1.181    0.066   17.867    0.000    1.181    0.765
   .Q_13              1.590    0.098   16.216    0.000    1.590    0.580
   .Q_15              1.766    0.102   17.402    0.000    1.766    0.702
   .Q_12              1.175    0.069   16.969    0.000    1.175    0.601
   .Q_24              1.197    0.069   17.326    0.000    1.197    0.642
   .Q_27              1.626    0.092   17.723    0.000    1.626    0.704
   .Q_28              1.451    0.084   17.360    0.000    1.451    0.654
   .Q_31              3.401    0.187   18.149    0.000    3.401    0.767
   .Q_32              1.187    0.067   17.621    0.000    1.187    0.677
   .Q_33              3.458    0.190   18.186    0.000    3.458    0.774
   .Q_34              2.399    0.137   17.482    0.000    2.399    0.665
   .Q_36              3.042    0.174   17.482    0.000    3.042    0.665
   .Q_37              1.706    0.095   17.992    0.000    1.706    0.738
   .Q_44              1.749    0.099   17.685    0.000    1.749    0.687
```

.Q_47	1.310	0.076	17.347	0.000	1.310	0.638
.Q_49	2.089	0.115	18.130	0.000	2.089	0.763
.Q_50	2.148	0.124	17.267	0.000	2.148	0.627
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000

EFA Two-Factor Oblique Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA2F, nfactors = 2, rotate = "oblimin", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1   MR2   h2   u2 com
Q_34   17  0.72 -0.12 0.46 0.54 1.1
Q_36   18  0.70 -0.11 0.43 0.57 1.0
Q_44   21  0.63  0.01 0.40 0.60 1.0
Q_12    7  0.62  0.08 0.44 0.56 1.0
Q_33   16  0.61 -0.12 0.32 0.68 1.1
Q_50   24  0.60  0.07 0.40 0.60 1.0
Q_32   15  0.56  0.06 0.35 0.65 1.0
Q_49   23  0.53 -0.08 0.25 0.75 1.0
Q_28   13  0.52  0.16 0.37 0.63 1.2
Q_39   20  0.48 -0.06 0.21 0.79 1.0
Q_47   22  0.47  0.19 0.34 0.66 1.3
Q_17    9  0.45  0.30 0.42 0.58 1.7
Q_24   10  0.44  0.24 0.34 0.66 1.6
Q_31   14  0.43  0.11 0.24 0.76 1.1
Q_27   12  0.42  0.27 0.35 0.65 1.7
Q_37   19  0.41  0.18 0.27 0.73 1.4
Q_26   11  0.41  0.02 0.18 0.82 1.0
Q_02    2 -0.15  0.66 0.37 0.63 1.1
Q_05    4 -0.04  0.64 0.39 0.61 1.0
Q_03    3  0.17  0.54 0.41 0.59 1.2
Q_01    1  0.12  0.54 0.36 0.64 1.1
Q_08    6 -0.02  0.53 0.27 0.73 1.0
Q_15    8  0.23  0.47 0.37 0.63 1.5
Q_06    5  0.20  0.44 0.32 0.68 1.4

                       MR1  MR2
SS loadings           5.43 2.83
Proportion Var        0.23 0.12
Cumulative Var        0.23 0.34
Proportion Explained  0.66 0.34
Cumulative Proportion 0.66 1.00

 With factor correlations of
     MR1  MR2
MR1 1.00 0.45
MR2 0.45 1.00

Mean item complexity =  1.2
Test of the hypothesis that 2 factors are sufficient.
```

```
The degrees of freedom for the null model are  276  and the objective function was
7.83 with Chi Square of  4582.31
The degrees of freedom for the model are 229  and the objective function was  1.21

The root mean square of the residuals (RMSR) is  0.04
The df corrected root mean square of the residuals is  0.05

The harmonic number of observations is  595 with the empirical chi square  649.04
with prob <  7.9e-42
The total number of observations was  595  with Likelihood Chi Square =  707.06  with
prob <  3.2e-50

Tucker Lewis Index of factoring reliability =  0.866
RMSEA index =  0.059  and the 90 % confidence intervals are  0.054 0.064
BIC =  -755.92
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                   MR1  MR2
Correlation of (regression) scores with factors   0.94 0.90
Multiple R square of scores with factors          0.89 0.81
Minimum correlation of possible factor scores     0.79 0.61

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.1076665
number of absolute residuals > 0.05 =  190
Proportion of absolute residuals > 0.05 =  0.6884058
```

EFA Two-Factor Oblique Model CFA

```
lavaan 0.6-7 ended normally after 25 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         46

  Number of observations                           728

Model Test User Model:

  Test statistic                               494.315
  Degrees of freedom                               185
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              4621.865
```

```
  Degrees of freedom                               210
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.930
  Tucker-Lewis Index (TLI)                       0.920

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -26789.792
  Loglikelihood unrestricted model (H1)     -26542.295

  Akaike (AIC)                               53671.584
  Bayesian (BIC)                             53882.738
  Sample-size adjusted Bayesian (BIC)        53736.674

Root Mean Square Error of Approximation:

  RMSEA                                          0.048
  90 Percent confidence interval - lower         0.043
  90 Percent confidence interval - upper         0.053
  P-value RMSEA <= 0.05                          0.738

Standardized Root Mean Square Residual:

  SRMR                                           0.044

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.030    0.066   15.709    0.000    1.030    0.592
    Q_02              1.076    0.063   17.193    0.000    1.076    0.637
    Q_03              1.087    0.057   19.217    0.000    1.087    0.697
    Q_05              1.079    0.064   16.765    0.000    1.079    0.624
    Q_06              0.575    0.043   13.406    0.000    0.575    0.517
    Q_08              0.629    0.048   13.096    0.000    0.629    0.506
  Support =~
    Q_12              0.894    0.049   18.160    0.000    0.894    0.639
```

```
    Q_17              1.018    0.054   18.727    0.000    1.018    0.654
    Q_24              0.829    0.049   17.034    0.000    0.829    0.608
    Q_27              0.859    0.055   15.575    0.000    0.859    0.565
    Q_28              0.877    0.054   16.345    0.000    0.877    0.588
    Q_31              1.006    0.078   12.842    0.000    1.006    0.478
    Q_32              0.740    0.048   15.418    0.000    0.740    0.559
    Q_33              0.976    0.079   12.360    0.000    0.976    0.462
    Q_34              1.113    0.068   16.285    0.000    1.113    0.586
    Q_36              1.221    0.077   15.785    0.000    1.221    0.571
    Q_37              0.785    0.056   14.045    0.000    0.785    0.516
    Q_44              0.879    0.058   15.154    0.000    0.879    0.551
    Q_47              0.863    0.051   16.872    0.000    0.863    0.602
    Q_49              0.779    0.062   12.633    0.000    0.779    0.471
    Q_50              1.111    0.066   16.817    0.000    1.111    0.600

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_34 ~~
   .Q_36              1.024    0.118    8.681    0.000    1.024    0.379
 .Q_12 ~~
   .Q_28              0.392    0.056    6.940    0.000    0.392    0.302
 .Q_24 ~~
   .Q_27              0.369    0.058    6.401    0.000    0.369    0.272
  Structure ~~
    Support           0.613    0.032   19.333    0.000    0.613    0.613

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.971    0.120   16.462    0.000    1.971    0.650
   .Q_02              1.692    0.107   15.747    0.000    1.692    0.594
   .Q_03              1.248    0.086   14.467    0.000    1.248    0.514
   .Q_05              1.823    0.114   15.969    0.000    1.823    0.610
   .Q_06              0.906    0.052   17.311    0.000    0.906    0.733
   .Q_08              1.148    0.066   17.407    0.000    1.148    0.744
   .Q_12              1.157    0.068   17.072    0.000    1.157    0.591
   .Q_17              1.388    0.082   16.992    0.000    1.388    0.573
   .Q_24              1.175    0.068   17.380    0.000    1.175    0.631
   .Q_27              1.572    0.089   17.691    0.000    1.572    0.681
   .Q_28              1.451    0.083   17.503    0.000    1.451    0.654
   .Q_31              3.423    0.188   18.247    0.000    3.423    0.772
   .Q_32              1.206    0.068   17.807    0.000    1.206    0.688
   .Q_33              3.513    0.192   18.315    0.000    3.513    0.787
   .Q_34              2.372    0.135   17.572    0.000    2.372    0.657
   .Q_36              3.085    0.175   17.674    0.000    3.085    0.674
   .Q_37              1.696    0.094   18.058    0.000    1.696    0.733
```

.Q_44	1.774	0.099	17.858	0.000	1.774	0.697
.Q_47	1.311	0.075	17.490	0.000	1.311	0.638
.Q_49	2.130	0.117	18.277	0.000	2.130	0.778
.Q_50	2.191	0.125	17.503	0.000	2.191	0.640
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000

EFA Three-Factor Orthogonal Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA3F, nfactors = 3, rotate = "varimax", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1   MR2   MR3   h2   u2 com
Q_34   20  0.68  0.08  0.03 0.46 0.54 1.0
Q_36   21  0.65  0.09  0.00 0.43 0.57 1.0
Q_12    9  0.62  0.25  0.06 0.45 0.55 1.3
Q_44   24  0.61  0.18  0.03 0.41 0.59 1.2
Q_50   27  0.59  0.23  0.02 0.40 0.60 1.3
Q_33   19  0.57  0.05  0.14 0.34 0.66 1.1
Q_32   18  0.56  0.20  0.11 0.36 0.64 1.3
Q_28   15  0.54  0.29 -0.01 0.38 0.62 1.5
Q_49   26  0.50  0.08  0.04 0.26 0.74 1.1
Q_47   25  0.49  0.31 -0.03 0.33 0.67 1.7
Q_24   13  0.46  0.36 -0.10 0.35 0.65 2.0
Q_27   14  0.45  0.38 -0.11 0.36 0.64 2.1
Q_39   23  0.45  0.06  0.03 0.21 0.79 1.0
Q_37   22  0.42  0.28 -0.07 0.26 0.74 1.8
Q_31   17  0.42  0.23 -0.17 0.26 0.74 1.9
Q_05    5  0.09  0.63  0.12 0.42 0.58 1.1
Q_02    2 -0.02  0.62 -0.01 0.38 0.62 1.0
Q_01    1  0.23  0.58  0.02 0.39 0.61 1.3
Q_03    3  0.27  0.57 -0.03 0.40 0.60 1.4
Q_15   11  0.31  0.52 -0.06 0.37 0.63 1.7
Q_08    7  0.08  0.51  0.13 0.28 0.72 1.2
Q_06    6  0.27  0.48  0.08 0.31 0.69 1.7
Q_13   10  0.36  0.44 -0.08 0.33 0.67 2.0
Q_09    8 -0.06 -0.03  0.75 0.57 0.43 1.0
Q_22   12  0.19  0.06  0.49 0.28 0.72 1.3
Q_04    4 -0.17 -0.03  0.41 0.19 0.81 1.3
Q_29   16  0.13  0.09  0.41 0.19 0.81 1.3

                       MR1  MR2  MR3
SS loadings           4.89 3.20 1.28
Proportion Var        0.18 0.12 0.05
Cumulative Var        0.18 0.30 0.35
Proportion Explained  0.52 0.34 0.14
Cumulative Proportion 0.52 0.86 1.00

Mean item complexity =  1.4
Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the null model are  351  and the objective function was
8.2 with Chi Square of  4791.26
```

```
The degrees of freedom for the model are 273  and the objective function was  1.29

The root mean square of the residuals (RMSR) is  0.04
The df corrected root mean square of the residuals is  0.05

The harmonic number of observations is  595 with the empirical chi square  692.55
with prob <  2.7e-38
The total number of observations was  595  with Likelihood Chi Square =  749.15  with
prob <  5.4e-46

Tucker Lewis Index of factoring reliability =  0.862
RMSEA index =  0.054  and the 90 % confidence intervals are  0.05 0.059
BIC =  -994.93
Fit based upon off diagonal values = 0.97
Measures of factor score adequacy
                                                   MR1  MR2  MR3
Correlation of (regression) scores with factors   0.92 0.88 0.83
Multiple R square of scores with factors          0.84 0.77 0.69
Minimum correlation of possible factor scores     0.69 0.55 0.39

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.04071908
number of absolute residuals > 0.05 =  73
Proportion of absolute residuals > 0.05 =  0.2079772
```

EFA Three-Factor Orthogonal Model CFA

```
lavaan 0.6-7 ended normally after 30 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         58

  Number of observations                           728

Model Test User Model:

  Test statistic                               792.092
  Degrees of freedom                               293
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              5304.567
  Degrees of freedom                               325
  P-value                                        0.000
```

```
User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.900
  Tucker-Lewis Index (TLI)                       0.889

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -33942.884
  Loglikelihood unrestricted model (H1)     -33546.293

  Akaike (AIC)                               68001.768
  Bayesian (BIC)                             68268.006
  Sample-size adjusted Bayesian (BIC)        68083.838

Root Mean Square Error of Approximation:

  RMSEA                                          0.048
  90 Percent confidence interval - lower         0.044
  90 Percent confidence interval - upper         0.052
  P-value RMSEA <= 0.05                          0.736

Standardized Root Mean Square Residual:

  SRMR                                           0.055

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.066    0.064   16.761    0.000    1.066    0.612
    Q_02              0.995    0.062   16.011    0.000    0.995    0.590
    Q_03              1.016    0.056   18.125    0.000    1.016    0.652
    Q_05              1.070    0.063   17.002    0.000    1.070    0.619
    Q_06              0.556    0.042   13.172    0.000    0.556    0.500
    Q_08              0.602    0.047   12.709    0.000    0.602    0.484
    Q_13              1.073    0.060   17.993    0.000    1.073    0.648
    Q_15              0.866    0.059   14.596    0.000    0.866    0.546
  Support =~
    Q_12              0.885    0.050   17.796    0.000    0.885    0.632
```

```
    Q_24              0.814    0.049   16.556    0.000    0.814    0.597
    Q_27              0.826    0.056   14.779    0.000    0.826    0.544
    Q_28              0.877    0.054   16.259    0.000    0.877    0.589
    Q_31              1.016    0.079   12.913    0.000    1.016    0.482
    Q_32              0.753    0.048   15.660    0.000    0.753    0.569
    Q_33              1.006    0.079   12.717    0.000    1.006    0.476
    Q_34              1.101    0.069   15.966    0.000    1.101    0.579
    Q_36              1.240    0.078   15.983    0.000    1.240    0.580
    Q_37              0.779    0.056   13.835    0.000    0.779    0.512
    Q_44              0.893    0.058   15.362    0.000    0.893    0.560
    Q_47              0.863    0.051   16.776    0.000    0.863    0.602
    Q_49              0.805    0.062   13.043    0.000    0.805    0.487
    Q_50              1.129    0.066   17.069    0.000    1.129    0.610
  Independence =~
    Q_04              0.884    0.092    9.615    0.000    0.884    0.448
    Q_09              1.185    0.093   12.741    0.000    1.185    0.639
    Q_22              0.992    0.085   11.732    0.000    0.992    0.568
    Q_29              0.755    0.086    8.738    0.000    0.755    0.407

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_34 ~~
   .Q_36              1.018    0.119    8.567    0.000    1.018    0.377
 .Q_12 ~~
   .Q_28              0.400    0.057    6.959    0.000    0.400    0.306
 .Q_24 ~~
   .Q_27              0.409    0.060    6.853    0.000    0.409    0.293
  Structure ~~
    Support           0.668    0.029   23.344    0.000    0.668    0.668
    Independence      0.058    0.052    1.103    0.270    0.058    0.058
  Support ~~
    Independence      0.096    0.051    1.888    0.059    0.096    0.096

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.895    0.113   16.710    0.000    1.895    0.625
   .Q_02              1.858    0.109   16.972    0.000    1.858    0.652
   .Q_03              1.397    0.086   16.159    0.000    1.397    0.575
   .Q_05              1.842    0.111   16.620    0.000    1.842    0.616
   .Q_06              0.927    0.052   17.763    0.000    0.927    0.750
   .Q_08              1.181    0.066   17.866    0.000    1.181    0.765
   .Q_13              1.591    0.098   16.217    0.000    1.591    0.580
   .Q_15              1.766    0.102   17.402    0.000    1.766    0.702
   .Q_12              1.174    0.069   16.965    0.000    1.174    0.600
   .Q_24              1.200    0.069   17.341    0.000    1.200    0.644
```

.Q_27	1.627	0.092	17.728	0.000	1.627	0.704
.Q_28	1.450	0.084	17.356	0.000	1.450	0.653
.Q_31	3.403	0.187	18.151	0.000	3.403	0.767
.Q_32	1.186	0.067	17.621	0.000	1.186	0.677
.Q_33	3.454	0.190	18.183	0.000	3.454	0.773
.Q_34	2.399	0.137	17.483	0.000	2.399	0.664
.Q_36	3.039	0.174	17.479	0.000	3.039	0.664
.Q_37	1.706	0.095	17.993	0.000	1.706	0.738
.Q_44	1.749	0.099	17.688	0.000	1.749	0.687
.Q_47	1.310	0.076	17.349	0.000	1.310	0.638
.Q_49	2.089	0.115	18.130	0.000	2.089	0.763
.Q_50	2.149	0.124	17.271	0.000	2.149	0.628
.Q_04	3.109	0.195	15.954	0.000	3.109	0.799
.Q_09	2.031	0.197	10.310	0.000	2.031	0.591
.Q_22	2.070	0.161	12.823	0.000	2.070	0.678
.Q_29	2.873	0.173	16.643	0.000	2.873	0.835
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000
Independence	1.000				1.000	1.000

EFA Three-Factor Oblique Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA3F, nfactors = 3, rotate = "oblimin", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1   MR3   MR2   h2   u2 com
Q_34   20  0.72 -0.11  0.01 0.46 0.54 1.0
Q_36   21  0.69 -0.10 -0.01 0.43 0.57 1.0
Q_12    9  0.63  0.08  0.01 0.45 0.55 1.0
Q_44   23  0.63  0.01  0.01 0.40 0.60 1.0
Q_33   19  0.61 -0.09  0.15 0.35 0.65 1.2
Q_50   26  0.61  0.07  0.00 0.41 0.59 1.0
Q_32   18  0.57  0.07  0.08 0.37 0.63 1.1
Q_28   15  0.53  0.15 -0.03 0.37 0.63 1.2
Q_49   25  0.52 -0.06  0.02 0.25 0.75 1.0
Q_39   22  0.48 -0.05  0.00 0.21 0.79 1.0
Q_47   24  0.47  0.19 -0.05 0.34 0.66 1.3
Q_17   11  0.47  0.26 -0.21 0.46 0.54 2.0
Q_24   13  0.42  0.22 -0.11 0.33 0.67 1.6
Q_27   14  0.41  0.26 -0.12 0.35 0.65 1.9
Q_31   17  0.41  0.11 -0.18 0.26 0.74 1.5
Q_02    2 -0.14  0.66 -0.03 0.38 0.62 1.1
Q_05    5 -0.03  0.66  0.11 0.42 0.58 1.1
Q_03    3  0.18  0.56 -0.06 0.44 0.56 1.2
Q_01    1  0.13  0.54  0.02 0.37 0.63 1.1
Q_08    7  0.00  0.53  0.10 0.29 0.71 1.1
Q_06    6  0.20  0.44  0.04 0.31 0.69 1.4
Q_09    8 -0.03  0.05  0.73 0.53 0.47 1.0
Q_22   12  0.22  0.03  0.50 0.29 0.71 1.4
Q_04    4 -0.16  0.04  0.42 0.20 0.80 1.3
Q_29   16  0.15  0.08  0.41 0.20 0.80 1.3
Q_16   10 -0.02 -0.03  0.41 0.17 0.83 1.0

                       MR1  MR3  MR2
SS loadings           5.05 2.51 1.46
Proportion Var        0.19 0.10 0.06
Cumulative Var        0.19 0.29 0.35
Proportion Explained  0.56 0.28 0.16
Cumulative Proportion 0.56 0.84 1.00

 With factor correlations of
      MR1   MR3   MR2
MR1  1.00  0.43 -0.05
MR3  0.43  1.00 -0.06
MR2 -0.05 -0.06  1.00
```

```
Mean item complexity =  1.2
Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the null model are  325  and the objective function was
7.66 with Chi Square of  4479.93
The degrees of freedom for the model are 250  and the objective function was  1.12

The root mean square of the residuals (RMSR) is  0.04
The df corrected root mean square of the residuals is  0.04

The harmonic number of observations is  595 with the empirical chi square  587.19
with prob <  3.6e-29
The total number of observations was  595  with Likelihood Chi Square =  652.88  with
prob <  9.3e-38

Tucker Lewis Index of factoring reliability =  0.873
RMSEA index =  0.052  and the 90 % confidence intervals are  0.047 0.057
BIC =  -944.26
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                   MR1  MR3  MR2
Correlation of (regression) scores with factors   0.94 0.89 0.84
Multiple R square of scores with factors          0.89 0.79 0.70
Minimum correlation of possible factor scores     0.78 0.59 0.41

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.0888666
number of absolute residuals > 0.05 =  167
Proportion of absolute residuals > 0.05 =  0.5138462
```

EFA Three-Factor Oblique Model CFA

```
lavaan 0.6-7 ended normally after 29 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         54

  Number of observations                           728

Model Test User Model:

  Test statistic                               627.576
  Degrees of freedom                               246
  P-value (Chi-square)                           0.000
```

```
Model Test Baseline Model:

  Test statistic                              4869.529
  Degrees of freedom                               276
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.917
  Tucker-Lewis Index (TLI)                       0.907

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -31372.213
  Loglikelihood unrestricted model (H1)     -31057.993

  Akaike (AIC)                               62852.425
  Bayesian (BIC)                             63100.302
  Sample-size adjusted Bayesian (BIC)        62928.835

Root Mean Square Error of Approximation:

  RMSEA                                          0.046
  90 Percent confidence interval - lower         0.042
  90 Percent confidence interval - upper         0.051
  P-value RMSEA <= 0.05                          0.918

Standardized Root Mean Square Residual:

  SRMR                                           0.056

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.030    0.066   15.709    0.000    1.030    0.591
    Q_02              1.076    0.063   17.194    0.000    1.076    0.637
    Q_03              1.087    0.057   19.227    0.000    1.087    0.697
    Q_05              1.081    0.064   16.799    0.000    1.081    0.625
    Q_06              0.574    0.043   13.383    0.000    0.574    0.516
```

```
    Q_08              0.629    0.048   13.098    0.000    0.629    0.506
  Support =~
    Q_12              0.895    0.049   18.093    0.000    0.895    0.640
    Q_17              1.017    0.055   18.645    0.000    1.017    0.653
    Q_24              0.827    0.049   16.899    0.000    0.827    0.606
    Q_27              0.858    0.055   15.480    0.000    0.858    0.564
    Q_28              0.866    0.054   16.038    0.000    0.866    0.581
    Q_31              1.011    0.079   12.877    0.000    1.011    0.480
    Q_32              0.730    0.048   15.121    0.000    0.730    0.551
    Q_33              0.986    0.079   12.459    0.000    0.986    0.467
    Q_34              1.097    0.069   15.944    0.000    1.097    0.577
    Q_36              1.221    0.078   15.724    0.000    1.221    0.571
    Q_44              0.893    0.058   15.380    0.000    0.893    0.559
    Q_47              0.865    0.051   16.860    0.000    0.865    0.603
    Q_49              0.783    0.062   12.669    0.000    0.783    0.474
    Q_50              1.109    0.066   16.725    0.000    1.109    0.599
  Independence =~
    Q_04              0.976    0.090   10.887    0.000    0.976    0.495
    Q_09              1.257    0.089   14.054    0.000    1.257    0.678
    Q_16              0.987    0.090   10.981    0.000    0.987    0.499
    Q_22              0.850    0.079   10.717    0.000    0.850    0.487

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_34 ~~
   .Q_36              1.043    0.119    8.735    0.000    1.043    0.383
 .Q_12 ~~
   .Q_28              0.401    0.057    7.011    0.000    0.401    0.308
 .Q_24 ~~
   .Q_27              0.373    0.058    6.404    0.000    0.373    0.274
  Structure ~~
    Support           0.618    0.032   19.522    0.000    0.618    0.618
    Independence      0.010    0.052    0.191    0.849    0.010    0.010
  Support ~~
    Independence     -0.041    0.050   -0.827    0.408   -0.041   -0.041

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.971    0.120   16.470    0.000    1.971    0.650
   .Q_02              1.692    0.107   15.756    0.000    1.692    0.594
   .Q_03              1.248    0.086   14.476    0.000    1.248    0.514
   .Q_05              1.820    0.114   15.962    0.000    1.820    0.609
   .Q_06              0.907    0.052   17.323    0.000    0.907    0.734
   .Q_08              1.148    0.066   17.410    0.000    1.148    0.744
   .Q_12              1.156    0.068   16.956    0.000    1.156    0.591
```

.Q_17	1.389	0.082	16.875	0.000	1.389	0.573
.Q_24	1.179	0.068	17.298	0.000	1.179	0.633
.Q_27	1.575	0.089	17.616	0.000	1.575	0.682
.Q_28	1.469	0.084	17.465	0.000	1.469	0.662
.Q_31	3.411	0.188	18.187	0.000	3.411	0.769
.Q_32	1.220	0.069	17.784	0.000	1.220	0.696
.Q_33	3.493	0.191	18.250	0.000	3.493	0.782
.Q_34	2.407	0.137	17.548	0.000	2.407	0.667
.Q_36	3.085	0.175	17.595	0.000	3.085	0.674
.Q_44	1.750	0.099	17.730	0.000	1.750	0.687
.Q_47	1.307	0.075	17.385	0.000	1.307	0.636
.Q_49	2.123	0.117	18.219	0.000	2.123	0.776
.Q_50	2.195	0.126	17.420	0.000	2.195	0.641
.Q_04	2.938	0.191	15.384	0.000	2.938	0.755
.Q_09	1.854	0.192	9.633	0.000	1.854	0.540
.Q_16	2.930	0.192	15.283	0.000	2.930	0.751
.Q_22	2.331	0.150	15.557	0.000	2.331	0.763
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000
Independence	1.000				1.000	1.000

EFA Four-Factor Orthogonal Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA4F, nfactors = 4, rotate = "varimax", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1   MR2   MR4   MR3   h2   u2 com
Q_12    8  0.67  0.17  0.14  0.02 0.49 0.51 1.2
Q_44   25  0.65  0.10  0.13  0.04 0.45 0.55 1.1
Q_28   16  0.59  0.22  0.11 -0.01 0.41 0.59 1.3
Q_32   18  0.55  0.13  0.20  0.08 0.37 0.63 1.4
Q_24   14  0.53  0.30  0.04 -0.09 0.38 0.62 1.6
Q_47   26  0.53  0.23  0.09 -0.02 0.34 0.66 1.4
Q_50   28  0.51  0.22  0.30  0.02 0.40 0.60 2.1
Q_17   12  0.49  0.40  0.19 -0.20 0.48 0.52 2.6
Q_49   27  0.49  0.00  0.16  0.03 0.27 0.73 1.2
Q_39   23  0.47  0.01  0.10  0.03 0.23 0.77 1.1
Q_27   15  0.46  0.34  0.13 -0.11 0.36 0.64 2.2
Q_37   22  0.45  0.22  0.09 -0.06 0.26 0.74 1.6
Q_02    2  0.00  0.66  0.00 -0.03 0.43 0.57 1.0
Q_05    5  0.12  0.62  0.02  0.11 0.41 0.59 1.2
Q_01    1  0.23  0.56  0.11  0.02 0.38 0.62 1.4
Q_03    3  0.27  0.55  0.13 -0.05 0.40 0.60 1.6
Q_15   10  0.39  0.48  0.02 -0.07 0.39 0.61 2.0
Q_08    6  0.17  0.48 -0.06  0.12 0.28 0.72 1.4
Q_40   24  0.01  0.46  0.15  0.16 0.25 0.75 1.5
Q_13    9  0.34  0.45  0.17 -0.08 0.35 0.65 2.3
Q_36   21  0.36  0.15  0.72 -0.02 0.67 0.33 1.6
Q_34   20  0.45  0.09  0.60  0.00 0.57 0.43 1.9
Q_33   19  0.34  0.10  0.54  0.16 0.44 0.56 2.0
Q_09    7 -0.07 -0.01  0.01  0.73 0.54 0.46 1.0
Q_22   13  0.16  0.08  0.09  0.50 0.30 0.70 1.3
Q_29   17  0.15  0.08  0.02  0.41 0.20 0.80 1.3
Q_04    4 -0.12 -0.03 -0.11  0.41 0.20 0.80 1.4
Q_16   11 -0.11  0.00  0.07  0.41 0.18 0.82 1.2

                       MR1  MR2  MR4  MR3
SS loadings           4.41 2.98 1.57 1.46
Proportion Var        0.16 0.11 0.06 0.05
Cumulative Var        0.16 0.26 0.32 0.37
Proportion Explained  0.42 0.29 0.15 0.14
Cumulative Proportion 0.42 0.71 0.86 1.00

Mean item complexity =  1.5
Test of the hypothesis that 4 factors are sufficient.
```

```
The degrees of freedom for the null model are  378  and the objective function was
8.53 with Chi Square of  4981.18
The degrees of freedom for the model are 272  and the objective function was  0.97

The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.04

The harmonic number of observations is  595 with the empirical chi square  464.66
with prob <  2.9e-12
The total number of observations was  595  with Likelihood Chi Square =  561.94  with
prob <  2.5e-22

Tucker Lewis Index of factoring reliability =  0.912
RMSEA index =  0.042  and the 90 % confidence intervals are  0.037 0.047
BIC =  -1175.75
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                   MR1  MR2  MR4  MR3
Correlation of (regression) scores with factors   0.89 0.88 0.83 0.84
Multiple R square of scores with factors          0.79 0.77 0.68 0.71
Minimum correlation of possible factor scores     0.58 0.54 0.37 0.41

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.03214013
number of absolute residuals > 0.05 =  40
Proportion of absolute residuals > 0.05 =  0.1058201
```

EFA Four-Factor Orthogonal Model CFA

```
lavaan 0.6-7 ended normally after 30 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         60

  Number of observations                           728

Model Test User Model:

  Test statistic                               836.586
  Degrees of freedom                               291
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                              5575.862
```

```
  Degrees of freedom                               325
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.896
  Tucker-Lewis Index (TLI)                       0.884

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -34038.938
  Loglikelihood unrestricted model (H1)     -33620.069

  Akaike (AIC)                               68197.876
  Bayesian (BIC)                             68473.294
  Sample-size adjusted Bayesian (BIC)        68282.775

Root Mean Square Error of Approximation:

  RMSEA                                          0.051
  90 Percent confidence interval - lower         0.047
  90 Percent confidence interval - upper         0.055
  P-value RMSEA <= 0.05                          0.368

Standardized Root Mean Square Residual:

  SRMR                                           0.059

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.054    0.064   16.545    0.000    1.054    0.605
    Q_02              0.988    0.062   15.882    0.000    0.988    0.585
    Q_03              0.991    0.056   17.584    0.000    0.991    0.636
    Q_05              1.051    0.063   16.635    0.000    1.051    0.608
    Q_08              0.595    0.047   12.546    0.000    0.595    0.479
    Q_13              1.111    0.059   18.821    0.000    1.111    0.671
    Q_15              0.885    0.059   14.996    0.000    0.885    0.558
    Q_40              0.853    0.072   11.798    0.000    0.853    0.453
```

```
  Support =~
    Q_12              0.899    0.049   18.246    0.000    0.899    0.643
    Q_17              1.041    0.054   19.251    0.000    1.041    0.669
    Q_24              0.839    0.049   17.240    0.000    0.839    0.614
    Q_27              0.861    0.055   15.577    0.000    0.861    0.566
    Q_28              0.882    0.054   16.438    0.000    0.882    0.592
    Q_32              0.723    0.048   14.980    0.000    0.723    0.546
    Q_37              0.784    0.056   13.994    0.000    0.784    0.515
    Q_44              0.875    0.058   15.055    0.000    0.875    0.548
    Q_47              0.862    0.051   16.825    0.000    0.862    0.601
    Q_49              0.770    0.062   12.458    0.000    0.770    0.466
    Q_50              1.114    0.066   16.853    0.000    1.114    0.602
  Independence =~
    Q_04              0.974    0.089   10.883    0.000    0.974    0.494
    Q_09              1.258    0.089   14.112    0.000    1.258    0.679
    Q_16              0.989    0.090   11.020    0.000    0.989    0.500
    Q_22              0.850    0.079   10.730    0.000    0.850    0.486
  Resources =~
    Q_33              1.134    0.081   14.011    0.000    1.134    0.537
    Q_34              1.418    0.068   20.723    0.000    1.418    0.747
    Q_36              1.656    0.077   21.616    0.000    1.656    0.774

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_12 ~~
   .Q_28              0.383    0.056    6.792    0.000    0.383    0.297
 .Q_24 ~~
   .Q_27              0.360    0.058    6.259    0.000    0.360    0.267
  Structure ~~
    Support           0.708    0.027   26.114    0.000    0.708    0.708
    Independence      0.009    0.051    0.175    0.861    0.009    0.009
    Resources         0.510    0.038   13.319    0.000    0.510    0.510
  Support ~~
    Independence     -0.060    0.050   -1.191    0.233   -0.060   -0.060
    Resources         0.749    0.027   27.576    0.000    0.749    0.749
  Independence ~~
    Resources         0.030    0.053    0.573    0.567    0.030    0.030

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.921    0.114   16.813    0.000    1.921    0.634
   .Q_02              1.873    0.110   17.037    0.000    1.873    0.657
   .Q_03              1.447    0.088   16.419    0.000    1.447    0.596
   .Q_05              1.883    0.112   16.781    0.000    1.883    0.630
   .Q_08              1.190    0.066   17.914    0.000    1.190    0.771
```

.Q_13	1.508	0.095	15.869	0.000	1.508	0.550
.Q_15	1.732	0.100	17.307	0.000	1.732	0.689
.Q_40	2.819	0.156	18.064	0.000	2.819	0.795
.Q_12	1.148	0.068	16.976	0.000	1.148	0.587
.Q_17	1.340	0.080	16.755	0.000	1.340	0.553
.Q_24	1.159	0.067	17.271	0.000	1.159	0.622
.Q_27	1.569	0.089	17.641	0.000	1.569	0.679
.Q_28	1.441	0.083	17.424	0.000	1.441	0.649
.Q_32	1.230	0.069	17.857	0.000	1.230	0.702
.Q_37	1.698	0.094	18.038	0.000	1.698	0.734
.Q_44	1.781	0.100	17.842	0.000	1.781	0.699
.Q_47	1.312	0.075	17.453	0.000	1.312	0.639
.Q_49	2.143	0.117	18.280	0.000	2.143	0.783
.Q_50	2.184	0.125	17.446	0.000	2.184	0.638
.Q_04	2.942	0.191	15.430	0.000	2.942	0.756
.Q_09	1.853	0.192	9.672	0.000	1.853	0.539
.Q_16	2.927	0.191	15.286	0.000	2.927	0.750
.Q_22	2.332	0.150	15.583	0.000	2.332	0.763
.Q_33	3.179	0.186	17.127	0.000	3.179	0.712
.Q_34	1.598	0.126	12.674	0.000	1.598	0.443
.Q_36	1.834	0.159	11.533	0.000	1.834	0.401
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000
Independence	1.000				1.000	1.000
Resources	1.000				1.000	1.000

EFA Four-Factor Oblique Model EFA

```
Factor Analysis using method =  minres
Call: fa(r = Stu.EFA4F2, nfactors = 4, rotate = "oblimin", fm = "minres")
Standardized loadings (pattern matrix) based upon correlation matrix
     item   MR1   MR3   MR4   MR2   h2   u2 com
Q_12    8  0.66 -0.04  0.07  0.04 0.48 0.52 1.0
Q_44   23  0.66 -0.11  0.06  0.06 0.43 0.57 1.1
Q_24   13  0.62  0.10 -0.07 -0.06 0.40 0.60 1.1
Q_28   15  0.58  0.05  0.04  0.01 0.40 0.60 1.0
Q_14    9  0.54  0.07 -0.09 -0.04 0.28 0.72 1.1
Q_47   24  0.54  0.08  0.02 -0.01 0.35 0.65 1.0
Q_37   21  0.50  0.08  0.01 -0.05 0.29 0.71 1.1
Q_32   17  0.48 -0.02  0.17  0.09 0.36 0.64 1.3
Q_27   14  0.46  0.18  0.06 -0.10 0.37 0.63 1.4
Q_49   25  0.45 -0.15  0.14  0.04 0.25 0.75 1.4
Q_17   11  0.44  0.23  0.12 -0.19 0.46 0.54 2.1
Q_02    2 -0.09  0.69 -0.01 -0.05 0.44 0.56 1.0
Q_05    5  0.06  0.61 -0.02  0.10 0.42 0.58 1.1
Q_03    3  0.13  0.54  0.12 -0.07 0.43 0.57 1.3
Q_01    1  0.16  0.49  0.07  0.02 0.37 0.63 1.3
Q_40   22 -0.12  0.47  0.14  0.14 0.25 0.75 1.5
Q_08    6  0.19  0.46 -0.13  0.11 0.29 0.71 1.6
Q_36   20 -0.05  0.04  0.84 -0.05 0.68 0.32 1.0
Q_34   19  0.16 -0.05  0.67 -0.01 0.58 0.42 1.1
Q_33   18  0.05  0.02  0.61  0.14 0.44 0.56 1.1
Q_09    7 -0.05  0.03 -0.01  0.72 0.52 0.48 1.0
Q_22   12  0.14  0.03  0.07  0.52 0.30 0.70 1.2
Q_04    4 -0.04 -0.01 -0.13  0.42 0.20 0.80 1.2
Q_29   16  0.14  0.04  0.00  0.42 0.19 0.81 1.2
Q_16   10 -0.12  0.02  0.05  0.40 0.18 0.82 1.2

                       MR1  MR3  MR4  MR2
SS loadings           3.81 2.16 1.93 1.44
Proportion Var        0.15 0.09 0.08 0.06
Cumulative Var        0.15 0.24 0.32 0.37
Proportion Explained  0.41 0.23 0.21 0.15
Cumulative Proportion 0.41 0.64 0.85 1.00

 With factor correlations of
      MR1  MR3  MR4   MR2
MR1  1.00 0.41 0.60 -0.05
MR3  0.41 1.00 0.23  0.01
MR4  0.60 0.23 1.00  0.04
MR2 -0.05 0.01 0.04  1.00
```

```
Mean item complexity =  1.2
Test of the hypothesis that 4 factors are sufficient.

The degrees of freedom for the null model are  300  and the objective function was
7.11 with Chi Square of  4156.7
The degrees of freedom for the model are 206  and the objective function was  0.7

The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.04

The harmonic number of observations is  595 with the empirical chi square  338.04
with prob <  1.8e-08
The total number of observations was  595  with Likelihood Chi Square =  408.61  with
prob <  1.7e-15

Tucker Lewis Index of factoring reliability =  0.923
RMSEA index =  0.041  and the 90 % confidence intervals are  0.035 0.046
BIC =  -907.43
Fit based upon off diagonal values = 0.98
Measures of factor score adequacy
                                                  MR1  MR3  MR4  MR2
Correlation of (regression) scores with factors   0.93 0.88 0.91 0.84
Multiple R square of scores with factors          0.87 0.77 0.82 0.70
Minimum correlation of possible factor scores     0.73 0.55 0.65 0.40

Residual statistics (residual.stats function in Field et al. (2012, p. 787))
Root means squared residual =  0.1201081
number of absolute residuals > 0.05 =  174
Proportion of absolute residuals > 0.05 =  0.58
```

EFA Four-Factor Oblique Model CFA

```
lavaan 0.6-7 ended normally after 29 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of free parameters                         55

  Number of observations                           728

Model Test User Model:

  Test statistic                               663.445
  Degrees of freedom                               245
  P-value (Chi-square)                           0.000
```

```
Model Test Baseline Model:

  Test statistic                              4767.011
  Degrees of freedom                               276
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.907
  Tucker-Lewis Index (TLI)                       0.895

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)             -31498.692
  Loglikelihood unrestricted model (H1)     -31166.513

  Akaike (AIC)                               63107.384
  Bayesian (BIC)                             63359.851
  Sample-size adjusted Bayesian (BIC)        63185.209

Root Mean Square Error of Approximation:

  RMSEA                                          0.048
  90 Percent confidence interval - lower         0.044
  90 Percent confidence interval - upper         0.053
  P-value RMSEA <= 0.05                          0.709

Standardized Root Mean Square Residual:

  SRMR                                           0.056

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Structure =~
    Q_01              1.031    0.066   15.673    0.000    1.031    0.592
    Q_02              1.094    0.063   17.481    0.000    1.094    0.648
    Q_03              1.067    0.057   18.693    0.000    1.067    0.685
    Q_05              1.083    0.065   16.774    0.000    1.083    0.627
    Q_08              0.627    0.048   12.989    0.000    0.627    0.504
```

```
    Q_40              0.809    0.075   10.852    0.000    0.809    0.430
  Support =~
    Q_12              0.874    0.050   17.577    0.000    0.874    0.625
    Q_14              0.782    0.061   12.788    0.000    0.782    0.478
    Q_17              1.062    0.054   19.713    0.000    1.062    0.682
    Q_24              0.892    0.048   18.652    0.000    0.892    0.654
    Q_27              0.932    0.054   17.201    0.000    0.932    0.613
    Q_28              0.853    0.054   15.749    0.000    0.853    0.573
    Q_32              0.711    0.049   14.634    0.000    0.711    0.537
    Q_37              0.777    0.056   13.826    0.000    0.777    0.511
    Q_44              0.852    0.059   14.543    0.000    0.852    0.534
    Q_47              0.871    0.051   17.017    0.000    0.871    0.608
    Q_49              0.741    0.062   11.889    0.000    0.741    0.448
  Independence =~
    Q_04              0.972    0.089   10.864    0.000    0.972    0.493
    Q_09              1.257    0.089   14.126    0.000    1.257    0.678
    Q_16              0.988    0.090   11.018    0.000    0.988    0.500
    Q_22              0.853    0.079   10.774    0.000    0.853    0.488
  Resources =~
    Q_33              1.130    0.081   13.905    0.000    1.130    0.535
    Q_34              1.431    0.069   20.778    0.000    1.431    0.753
    Q_36              1.644    0.077   21.261    0.000    1.644    0.768

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
 .Q_12 ~~
   .Q_28              0.430    0.058    7.371    0.000    0.430    0.322
  Structure ~~
    Support           0.630    0.032   19.746    0.000    0.630    0.630
    Independence      0.035    0.053    0.667    0.504    0.035    0.035
    Resources         0.453    0.041   10.934    0.000    0.453    0.453
  Support ~~
    Independence     -0.063    0.050   -1.247    0.212   -0.063   -0.063
    Resources         0.725    0.028   25.677    0.000    0.725    0.725
  Independence ~~
    Resources         0.030    0.053    0.571    0.568    0.030    0.030

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .Q_01              1.968    0.120   16.371    0.000    1.968    0.649
   .Q_02              1.652    0.107   15.437    0.000    1.652    0.580
   .Q_03              1.290    0.088   14.646    0.000    1.290    0.531
   .Q_05              1.814    0.115   15.833    0.000    1.814    0.607
   .Q_08              1.151    0.066   17.375    0.000    1.151    0.746
   .Q_40              2.892    0.161   17.947    0.000    2.892    0.815
```

.Q_12	1.192	0.070	17.106	0.000	1.192	0.609
.Q_14	2.068	0.114	18.196	0.000	2.068	0.772
.Q_17	1.296	0.079	16.490	0.000	1.296	0.535
.Q_24	1.066	0.063	16.859	0.000	1.066	0.573
.Q_27	1.441	0.083	17.287	0.000	1.441	0.624
.Q_28	1.492	0.085	17.540	0.000	1.492	0.672
.Q_32	1.249	0.070	17.875	0.000	1.249	0.712
.Q_37	1.708	0.095	18.025	0.000	1.708	0.739
.Q_44	1.821	0.102	17.892	0.000	1.821	0.715
.Q_47	1.295	0.075	17.335	0.000	1.295	0.630
.Q_49	2.188	0.119	18.329	0.000	2.188	0.800
.Q_04	2.947	0.191	15.461	0.000	2.947	0.757
.Q_09	1.854	0.191	9.696	0.000	1.854	0.540
.Q_16	2.928	0.191	15.301	0.000	2.928	0.750
.Q_22	2.326	0.150	15.551	0.000	2.326	0.762
.Q_33	3.189	0.187	17.092	0.000	3.189	0.714
.Q_34	1.564	0.128	12.206	0.000	1.564	0.433
.Q_36	1.876	0.162	11.566	0.000	1.876	0.410
Structure	1.000				1.000	1.000
Support	1.000				1.000	1.000
Independence	1.000				1.000	1.000
Resources	1.000				1.000	1.000