Factors influencing first-year students' intention to continuously use the Skills Assessment Manager Online Learning Environment at the Central University of Technology, Free State

by

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Submitted in fulfilment of the requirements for the degree

MASTER OF

INFORMATION TECHNOLOGY

Department of Information Technology

Faculty of Engineering, Built Environment, and Information Technology

Central University of Technology, Free State

BLOEMFONTEIN

2022

Declaration

I, Hester Aletta Nortjé, declare that this dissertation, entitled Factors influencing first-year students' intention to continuously use the Skills Assessment Manager Online Learning Environment at the Central University of Technology, Free State, is a presentation of my own original research work conducted at the Central University of Technology, Free State. Wherever contributions of others were involved, every effort has been made to indicate this clearly, with due reference to the literature and acknowledgement of collaborative research and discussions. No part of this dissertation has been submitted for any other degree or professional qualification.

The work was conducted under the guidance of Ms M. Venter, Dr P.H. Potgieter and Mr C.H. Wessels.

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Hester Aletta Nortjé

4 October 2022

I certify that the above statement is correct

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4 October 2022

Acknowledgements

This project required a village to complete, not just any village, but one near and dear to my heart. This village comprises people hand-picked by the Good Lord Himself to provide every resource I needed. I am, therefore, grateful to have this small space in this large document to acknowledge the provider of all, our Heavenly Father, for being an inexhaustible source of strength, grace and comfort during this immensely challenging endeavour, as well as the provider of my extraordinary support system consisting of family, friends and colleagues.

I would like to express my sincerest gratitude to Ms M.I. Venter, Mr C.H. Wessels, Dr P.H. Potgieter and Prof. A. Fossey for their tireless support, assistance, guidance, encouragement, and faith in me to complete this study. In a million lifetimes, I could not have asked for a better team of people to have guided this project to fruition and to have taught me such a great deal along the way. Not only about research and writing, but also about myself.

No project could have existed had there not been a committee of seasoned researchers who put their faith in my proposal and supported it; therefore, I would like to sincerely thank the staff of the Faculty of Engineering, Built Environment, and Information Technology for their support in the form of tuition and funding.

This project would not have been as finely polished as it is right now had it not been for Hettie Human, who waved her expert language editing wand to clear up all the little things that one no longer sees after what felt like an eternity of writing; I am truly grateful.

Subsequently, there would be no healthy and well-looked-after Alesta to whom this project proudly belongs without a mother, father, sister, my best friend, and my fiancé, who spent many nights in prayer, and who dried tears, and provided support from the sidelines during the entire process; my sincerest gratitude to you all.

Another pair of human beings whose friendship and unwavering motivation impacted my ability to complete this project in many ways are N. Masana and S.L. Tom, to whom I would like to extend my sincere gratitude for their role in the successful collection of the data and their commitment to reminding me to put my studies first and to complete my research project, as they did before me.

Without willing participants, no data collection would have been possible; therefore, I would like to thank the first-year students in the basic digital literacy classes I taught, who were so kind as to spend 15 minutes of their precious time completing my survey before their final assessment for the subject. Your contribution will truly live on past your stay at the CUT and has had a more significant impact on my life than you could have imagined while completing Ms Nortje's survey for her studies in your DLC5011 class.

Lastly, I would like to thank Cengage for the fantastic online learning environment that not only conveniently served as the object of my research project, but also saved me so much time in terms of preparation for lectures and marking of assessments that made it possible for me to complete this research project while managing the 1 003 first-year students, of whom 793 responded to this project's survey.

Table of Contents

List of tables

List of figures

Abbreviations

AVE	Average variance extracted
AI	Artificial Intelligence
CUT	Central University of Technology
DED	Decomposed expectation-disconfirmation
EDT	Expectation-disconfirmation
HTMT	Heterotrait-monotrait
ECM	expectation-confirmation
ISS	Information systems success
IS-ECM	Information systems
MIC	Measurement instrument questionnaire
MOOC	Massive Open Online Course Platform
OLE	Online learning environments
PLS	Partial least squares
PLS-SEM	Partial least squares structural equation modelling
SEM	Structural equation modelling
STV	Subjective task value
TAM	Technology acceptance
TCT	Technology continuance
TTF	Task-technology fit
VIF	Variance inflation factor

Abstract

Introduction: With the rapid development of digital technologies, many tertiary education institutions have introduced online learning environments (OLEs) as a component of blended learning. These OLEs bring about possibilities to expand the student population beyond the limitations of the physical boundaries of traditional classroom-based learning. OLEs create interactive and engaging environments in which students have flexible access to learning materials and are able to study more independently in relation to time and place. Advances in new technologies in online learning have increased ubiquitous access, ease of use, functionality, and flexibility. Serious concerns with OLEs are a decline in student persistence in engagement with an OLE, and the likelihood of students dropping out of a course. Students who disengage from OLEs often fail to reap the benefits of the course content. Therefore, an understanding of the factors that influence students' intention to continuously engage with an OLE will provide information on how to optimise the OLE so that students can achieve maximum learning success. This study was, thus, undertaken to identify the factors that influence students' intention to continuously use the skills assessment manager (SAM) OLE implemented at the Central University of Technology, Free State, for the delivery of the module Basic Digital Literacy to all first-year students at the university.

Methods: In this three-phase study, a positivist approach was followed. In Phase 1, a literature search was undertaken to identify literature with relevant theories and factors that could be used to devise measurement models for the assessment of a structural model comprising of potential factors and the target factor *Continuous Use Intention*. In the structural model, linkages between potential factors and the target factor, *Continuous Use Intention,* were indicated. Thereafter, 13 relational hypotheses between factors were formulated for testing. In Phase 2, the factors were operationalised by specifying measurement models contained in a questionnaire with specific items (observable variables) relating to each factor (latent variables). To gather measurement data, the questionnaire was administered to 1 003 students, of whom 793 responded. The data were analysed using partial least squares structural equation modelling with the program SmartPLS, to assess the validity and reliability of the measurement models. In Phase 3, the structural model was validated and assessed, after which the relational hypotheses were tested using SmartPLS. Thereafter, the actual factors that influence students' intention to continuously use the OLE were identified.

Results: Because the structural model was free of collinearity issues, it could be assessed. Twelve of the 13 relational hypotheses were significant at $\alpha = 0.05$. These 12 relationships were used to construct

a revised structural model showing six actual factors in relationships with *Continuous Use Intention.* The actual factors, *Flow*, *Satisfaction* and *Perceived Usefulness,* explained 47.5% of *Continuous Use Intention.* The actual factors, *Confirmation*, *Perceived Ease of Use* and *Perceived Usefulness* explained 63.6% of *Satisfaction. Information Quality, Confirmation,* and *Perceived Ease of Use* explained 52.4% of *Perceived Usefulness. Information Quality,* and *Confirmation* explained 47.2% of *Perceived Ease of Use. Information Quality* explained 35.9% of *Confirmation.*

Significance: By identifying factors that influence students' intention to continuously engage with the SAM OLE while studying Basic Digital Literacy, these factors will inform decisions to optimise the OLE to maximise student learning success.

Keywords: continuous use intention, structural model; measurement models; partial least squares (PLS) structural equation modelling (SEM); smartPLS; skills assessment manager (SAM); online learning environment (OLE)

Chapter 1
Introduction to the study

1.1 Background to the study

Being digitally literate is one of the cornerstones of full participation in the present era of rapid technological advancement in the Fourth Industrial Revolution (4IR). Businesses that align themselves with this revolution also rely heavily on a workforce equipped with critical 21st-century knowledge and skills (Schwab, 2016). A workforce for this revolution requires knowledge and skills in fields such as artificial intelligence, automation, biotechnology, quantum computing, robotics, the internet of things, three-dimensional printing and other technologies. Therefore, employees who contribute successfully to the revolution have furnished themselves with relevant knowledge, especially digital literacy skills and digital technologies (Jang et al., 2021). Future employees need a solid digital literacy foundation, so that they are adequately prepared to play an active role in the 4IR work environment. These employees should be competent in digital technologies, to enable them to make significant contributions to productivity in the workplace. The World Economic Forum (2020) reports on the accelerated pace at which companies adopt new technologies. The prediction is that there will be a 6% increase in the likelihood that companies will adopt new technologies from 2018 to 2025. Additionally, the COVID-19 pandemic has emphasised the importance of fast-tracking technology adoption and digitalisation in the workplace (World Economic Forum, 2020).

One of the major perceived barriers to the adoption of digital technologies is a lack of digital skills in the labour market. A survey undertaken by the World Economic Forum across 26 countries revealed that 20 of these countries faced digital skills gaps in the local labour market, across industries and regions (Burger, 2019; Craig, 2019; World Economic Forum, 2020). This survey specifically highlights that people who demonstrate competencies in the use of technology possess skills that are highest in demand. Also considered high in demand are interpersonal and cognitive skills, such as those involving creativity, critical thinking, analysis, logical thinking and self-management. The survey also reveals that South African business executives indicated a 29% progression in the adoption of digital proficiency skills from 2019 to 2020. The inertia of tertiary education institutions in supporting the acquisition of broad-based and highly variable skills by the developing workforce is a major barrier for these graduates to play an effective and meaningful role in the 4IR (Myklebust & Smidt, 2021).

Facilitating digital literacy knowledge acquisition in preparation for the new and developing workplace requires educational institutions to adjust to student growth and development needs. The increased demand for technological developments requires educational institutions to become more flexible in curriculum development and positively inclined to introduce education tools to support students' digital literacy skills development (Jang et al., 2021). Digital skills development occurs across various educational settings, including formal education, non-formal provision of training, and self-directed learning (Broadband Commission for Sustainable Development, 2017).

In South Africa, formal education mainly occurs through primary and secondary schooling, while tertiary education occurs through universities and technical vocational education and training (TVET) institutions. In contrast, non-formal training occurs via after-school clubs, winter schools or on platforms such as Udemy or Master Class. Recently, a more self-directed approach to learning has become a popular method to acquire digital and technology skills. Certified online educational programmes, referred to as nanodegrees, are programmes designed in such a way as to develop the latest and typically more advanced skills in a short time(Siemens et al., 2015). The shortened time frame needed to obtain an advanced, high-demand skill enables people to work with the latest technological developments (Myklebust & Smidt, 2021). The skills developed through these online programmes include advanced skills in computer science, such as data science, programming and artificial intelligence.

Tertiary education institutions are traditionally slow to adapt to the ever-changing educational landscape. Today, many universities still apply delivery methods and pedagogies that have become irrelevant for the preparation of students for today's dynamic and changing workforce. Meeting the demands of the ever-changing and developing workplace of the 21st century necessitates educational institutions to adopt an approach to education that has a higher level of real-world authenticity than what is historically associated with them (Herrington & Herrington, 2007). The idea behind a more authentic approach to education is to provide students with a real-world context that reflects more realistically how their newly acquired knowledge will contribute to real-life situations in the 21st century. Although the approach to teaching and learning in higher education accommodates both face-to-face and web-based learning environments, web-based learning has become a more prominent feature in recent times, particularly for the acquisition of digital and technology-related skills (Moore et al., 2011). Therefore, as technology advances, a much richer learning experience is possible for the developing workforce.

Many tertiary education institutions have recognised the need to provide students with digital and technological skills. To bridge the gap from secondary to tertiary education, these institutions often provide introductory computer courses in students' first year. Many of these introductory courses address productivity software applications, such as the Microsoft Office Suite, Open suite and WPS Suite, which cover word processing and database applications, presentation software, and spreadsheets (Gallardo-Echenique et al., 2015; Piccoli et al., 2001). Typically, in the past, these introductory courses were delivered using traditional classroom-based learning, such as face-to-face lectures, practical exercises and tutorial sessions. However, with recent advances and developments in digital technology, face-to-face lectures alone are inadequate for students to master new technological developments (Koorsse et al., 2016). Thus, many tertiary education institutions have adopted a blended mode of delivering these introductory courses to their students, which involves the use of web-based online learning environments (OLEs) together with traditional classroom-based learning (Tang & Chaw, 2015). The implementation of these OLEs in a blended mode of delivery allows students to engage asynchronously, in other words, to learn at any time. Furthermore, this mode of learning also allows students to access up-to-date and relevant learning materials (Akkoyunlu & Yilmaz-Soylu, 2008; Anderson, 2009; Cengage Learning, 2017). For lecturers of these introductory courses, integrating OLEs in blended learning modules facilitates the grading and monitoring of student performance, thereby providing more thorough assessment (Matthews et al., 2012).

1.2 Problem statement

OLEs offer possibilities to expand the student population beyond the physical boundaries of the traditional, classroom-based learning environment. Therefore, students who are geographically distant from a tertiary education institution are able to participate in learning by accessing an OLE (Cidral et al., 2018). Furthermore, the adoption of OLEs by tertiary education institutions may bring about improved student access to education and training, and improve the quality of learning (Panigrahi et al., 2018). However, student retention in such OLEs remains a major challenge (Alkhaldi & Abualkishik, 2019; Roca et al., 2006; Spector & David et al., 2014; Venter & Swart, 2018; Yan et al., 2021).

To optimise students' academic performance in higher education, student retention in an OLE is essential. The more time spent using an OLE, the more ideal the opportunity for students to immerse themselves in the course content, and to achieve their learning outcomes. Students who disengage from OLEs often fail to reap the benefits of the course content (Thong et al., 2006). For these students, the OLE becomes a barrier to the achievement of learning success (Roca et al., 2006). You and Kang (2014) state that satisfaction is a crucial factor for students to adopt and accept the use of an OLE, and that students need to be continuously engaged with an OLE to achieve learning success. Although initial acceptance of an OLE is essential to achieve successful adoption; adoption success requires that the user continues to use the OLE (Daɫhan & Akkoyunlu, 2016).

At the Central University of Technology, Free State (CUT), it is considered compulsory for a first-year student registered for any qualification to develop digital literacy skills and gain a basic understanding of the use of computers and software programs. Therefore, all first-year students registered in the university's four faculties must complete a Basic and an Advanced Digital Literacy service module. The purpose of this module is to equip students with basic knowledge of computers and how to use the most commonly used productivity software applications. Productivity software is not only used in personal settings, but by businesses across industries around the world. In the Basic and Advanced Digital Literacy modules, students learn how to use the productivity software applications Word, Excel, PowerPoint, Outlook, and Access from the Microsoft Office Suite.

Approximately 2 000 CUT students from diverse backgrounds register for the Basic Digital Literacy module in the Information Technology Department every year. To accommodate such a large number of students, the delivery of this module is through a blended mode of delivery. In addition to face-to-face delivery, components of this module are delivered through the use of an OLE. From personal experience over the past six years, as one of the lecturers of the module, I found that student engagement does not remain optimal throughout the delivery of the module. I have noted a loss of student interest in the modules, dwindling student performances, and a steady decrease in the number of students engaging with the OLE. Thus, an understanding of the factors that influence student intention to continuously engage with the OLE of the Basic Digital Literacy module will provide information about how to optimise the OLE, so that maximum student learning success can be achieved.

Thus, the research question that underpins this study is the following:

> *Which factors influence students' intention to continuously use the OLE for Basic Digital Literacy at the CUT?*

In pursuit of providing an answer to this question, this study was undertaken to identify the factors that could predict first-year students' continuous intention to use the Microsoft Office Suite in the Basic Digital Literacy OLE of the module. Therefore, the main hypothesis posed for the study is as follows:

If the factors that predict students' intention to continuously use the OLE for Basic Digital Literacy are known, then the OLE can be optimised, so that students will have the intention to continuously use the OLE and achieve their learning outcomes.

Once these factors have been identified, it becomes possible to optimise the OLE and improve students' intention to use the OLE, leading to optimum student engagement, and improved attendance and pass rates.

1.3 Overview of methodology

In order to address the research question of the study, the researcher held a positivistic standpoint in relation to the research process. A deductive reasoning approach was followed, through which quantitative data were gathered and analysed in a multi-method sequential process. This process took place in three phases, namely the construction of a structural model, the assessment of the measurement models, and the assessment of the structural model. The phase in which the construction of the structural model took place entailed the review and scrutiny of relevant literature sources for their eligibility for inclusion in this study. The phases where the assessment of the measurement and structural models took place entailed the establishment of the validity and reliability of each of the models and the testing of the relational hypotheses. Throughout the assessment phases a statistical analysis software specifically suited to the analysis of quantitative data in studies where theory testing or development is present (Suzianti & Paramadini, 2021). Each of these phases was guided by a series of research sub-questions accompanied by several objectives (Chapter 3, 3.3 Conceptual framework, page 29).

1.4 Significance of the study

Understanding the factors that influence students' intention to continuously use the OLE for the Basic Digital Literacy module in the first year at CUT will facilitate the optimisation of the delivery style of the module. In addition, a clear understanding of these factors will inform decision-making when improvements are made to the OLE. Finally, it is expected that, with an optimised OLE, the overall student performance in Basic Digital Literacy will improve substantially.

1.5 Ethical Considerations

Ethical approval was obtained in 2018 from the Faculty Research and Innovation Committee of the Faculty of Engineering, Built Environment, and Information Technology at CUT, in accordance with the CUT Research Ethics and Integrity Framework (2016). The ethics approval reference number is FEIT 5/18 - 6:29/24-5-18. A copy of the ethics approval certificate is given in Appendix A (Ethical Considerations). Ethical approval was granted for the duration of the study for the measurement instrument questionnaire.

1.6 Limitations to the study

The research study was limited in several ways, due to physical location constraints and sample size implications. The data collection was bound to one learning institution in one country, for reasons related to budget and time constraints, as well as the logistical practicality of gathering data from a convenience sample. Not all factors could be included in this study, as including more factors would have implications for sourcing a larger sample size, which would have required more time to complete the study (Deng et al., 2018).

1.7 Outline of the dissertation

This dissertation is partitioned into seven chapters:

Chapter 1: Introduction

In this chapter, the background and context to the study was presented, together with the aim, main research question, the significance of the study and ethical considerations. Also presented in this chapter was an overview of the layout of the chapter.

Chapter 2: Literature review

In this chapter, a review of the literature will be presented. This review will cover the following topics: innovation in learning in higher education, blended learning, and digital learning platforms, as well as the theoretical foundation of the study. Also presented in this chapter will be a review of structural equation modelling (SEM), which was used in this study to specify a theoretical causal model.

Chapter 3: Study conceptualisation and methods

In this chapter, the conceptualisation will be defined, and the methods of the study will be described. In the conceptualisation of the study, the approach, conceptual framework, student population and materials will be defined. In the methods section of the study, the three phases of methods will be described. These three phases include the methods to construct the structural model, the assessment of the measurement models and the assessment of the structural model.

Chapter 4: Structural model for students' intention to continuously use the Skills Assessment Manager online learning environment

In this chapter, the results of the first phase of this study will be presented, which include the literature sources used in this study, the theories and potential factors extracted from the literature sources to construct the structural model, and the structural model and relational hypotheses.

Chapter 5: Validation of the measurement models

In this chapter, the results of the second phase of this study will be presented, which include the items used in the measurement instrument, a summary of biographical and supplemental information collected with the measurement instrument, and the validities and reliabilities of the measurement instrument.

Chapter 6: Actual factors that influence students' intention to continuously use the Skills Assessment Manager online learning environment

In this chapter, the results of the third phase of this study will be presented, which include the strength and significance of the hypothesised relationships and the identification of the actual factors that influenced students' intention to continuously use the SAM OLE.

Chapter 7: Discussion and concluding remarks

In this chapter, the results of this study will be interpreted and discussed in relation to the findings of similar studies in the field. Also, limitations to the study will be highlighted, as will future prospects and concluding remarks.

Chapter 2

Literature review of blended digital learning in higher education and theoretical foundation

2.1 Introduction

The higher education landscape is changing rapidly with the increasing popularity of online instruction. Due to advances in the development of information systems, university lecturers today have access to a wide range of teaching options. Developments in educational software, the use of computers in education, and access to distributed networks have culminated in many new teaching and learning configurations, and have brought about new learning experiences for students. Online education is one of the fastest growing areas of education technology. Popovici and Mironov (2015) report that global e-learning revenues have grown by over 900% since the year 2000, and have not yet reached their peak, as revenue is expected to increase threefold by 2025. The global e-learning investment market is estimated to reach \$336.98 billion by 2026. Internet-driven e-learning management systems make up over 29% of the total e-learning market share in the United States of America. These recent advances and changes in higher education learning options have also brought about many questions about the effectiveness of these new methods of educational delivery and the conditions that make it a successful learning experience for students (Willging & Johnson, 2019).

2.2 Innovation in learning in higher education

Since late in the previous century, digital solutions have been implemented gradually in higher education. Universities were among the earliest adopters of digital technologies and have become one of the foremost creators of new digital solutions for education (Bygstad et al., 2022; Iivari, 2015; Ryan, 2010; Sam & Van der Sijde, 2014). The motivation for universities to adopt digital technologies was primarily to improve their day-to-day operational efficiency, which resulted in universities moving from a more concrete position to a digital space (Ellis & Goodyear, 2016). Initially, universities digitised administration systems, such as student registers, examination systems, human resource recordkeeping, library indexing systems, and financial systems. Then, over the last two decades, the focus at universities shifted to the introduction of digital solutions in the educational environment (Holmberg, 2005; Johnson et al., 2015; Kumar et al., 2017; Kumari et al., 2020; Oncu & Cakir, 2011; Siemens et al., 2015). Universities gradually implemented digital solutions in the educational environment on two different levels. These solutions firstly dealt with communication amongst university departments, lecturers, and students; and secondly, with the digitisation of subject matter (Bygstad et al., 2022). Digitised courses were developed locally by academics as part of their discipline-specific teaching options (Crawford et al., 2020). A substantial amount of integration of digital solutions in higher education is currently ongoing; however, the COVID pandemic accelerated its integration on several fronts of education (Bygstad et al., 2022).

Digitisation in higher education involves several digital solutions being implemented in the student learning environment. These solutions include digital classrooms, digital whiteboards, video conferencing, and the provision of digital materials in the form of slideshows and videos. The management of digital systems in education through learning management systems has become the foundation for the management of digital learning at universities (Bygstad et al., 2022). Digital assignments, presentations and assessments have become an integral part of university student learning. Digital student learning in higher education is generally referred to as digital learning, which is either computer-based e-learning or internet-based e-learning (Moore et al., 2011; Tamm, 2021). Computer-based e-learning does not necessarily require an internet connection, whereas internet-based e-learning often depends solely on an internet connection to access digital learning. Internet-based e-learning is generally referred to as online learning.

2.3 Digital learning

Digital learning is an overarching term that includes any learning facilitated by any digital technology. Therefore, digital learning encompasses students using various multimedia tools, such as accessing and consuming digital knowledge through the internet, undertaking video conferencing and watching online videos during their studies. Students could be registered at traditional learning institutions, or may undertake self-regulated learning (Broadbent & Poon, 2015). Today, students registered at traditional learning institutions will be exposed to digital learning in some form, which means large components of their coursework are completed using the internet. This type of digital learning is generally referred to as online learning. Online learning implies that student learning includes learning through the internet as well as face-to-face interaction between student and lecturer (Bygstad et al., 2022). Students can, thus, engage with coursework in a classroom or from a distance. The use of the internet at universities allows for new pedagogical implementations to emerge, leading to innovative ideas coming to the forefront, and brings about the development and expansion of new teaching modes (Zhang et al., 2021).

When a course is taken solely over the internet, entirely online, this type of learning is called virtual learning or e-learning. Historically, e-learning was known as distance learning, to emphasise that geographical distance is not a barrier to learning (Cho et al., 2015). As the barrier of physical distance no longer restricted learning, it meant that students from any country in the world could participate in the same course. In this e-learning space, students do not meet with a lecturer face-to-face, but, instead, communicate digitally through email, forums, chats, or video conferencing. Blended learning, on the other hand, takes place in different modalities: traditional classroom learning is combined with e-learning or online learning (Müller & Mildenberger, 2021). In the blended learning space, students are required to be physically present in a classroom for some portions of the coursework, while other portions are completed online.

2.4 Blended learning

Since the advent of online learning, universities have widely adopted blended learning. The term blended learning is often used interchangeably with terms such as mixed-mode, hybrid learning, or flexible learning (Müller & Mildenberger, 2021). In blended learning environments, learning materials are made available digitally or through the Internet (Lin & Wang, 2012). Besides the face-to-face learning environments, the online learning modality in blended learning implies that students are engaged in self-learning and collaborate with other students in the course. The combination of the two learning modalities is also known as asynchronous learning (Wang et al., 2017). Therefore, blended learning combines traditional physical classes and aspects of virtual learning (Akkoyunlu & Yilmaz-Soylu, 2008; Lin & Wang, 2012). Students receive face-to-face teaching but are also expected to self-manage their learning using digital platforms, interact with peers and lecturers, monitor progress, and check due dates for assignments and assessments (Lin & Wang, 2012). Blended learning, thus, includes all digitally supported learning environments, apart from pure online learning and pure classroom instruction (Müller & Mildenberger, 2021).

Historically, online learning was implemented to supplement formal education. For example, in 1995, the Computer Assisted Learning Center Campus in New Hampshire, USA, started using the internet fully to present instruction, learning materials and administration, making it possible for students and lecturers to interact in real-time (Zhang et al., 2021). In 1993, Jones International University became the first university in the USA to be fully web-based. Since the nineties, many universities have offered qualifications using different internet modalities and are applied in different ratios. Müller and Mildenberger (2021) state that the online proportion of a blended learning course should be between 30 and 79% of content delivery. However, other authors have suggested that the proportion of online instruction to classroom instruction should maintain a one-to-one ratio (Bernard et al., 2009), as students tend to prefer high and medium online proportions rather than low or supplementary online portions (Asarta & Schmidt, 2020; Hilliard & Stewart, 2019; Owston & York, 2018). However, the concern is that blended learning may cause an increase in the workload beyond the workload of a traditional course, resulting in the so-called "course-and-a-half" syndrome (Garrison & Vaughan, 2012).

The technologies employed in the delivery of online learning have evolved substantially in recent times. These technologies can be divided into asynchronous and synchronous online learning (Ji et al., 2022). Examples of asynchronous learning include discussion boards, blogs, and podcasts – lecturers and students do not communicate simultaneously. In asynchronous online learning, students in separate class arrangements are able to study independently, at varying times and in varying geographically distant locations, without real-time communication between instructors and students (Tamm, 2021). In synchronous online learning, various communication technologies, such as chatrooms and videoconferencing, allow lecturers and students to communicate and interact in real-time. Because synchronous online learning closely resembles face-to-face instruction, an increasing number of higher education institutions are moving towards the implementation of this type of learning instruction (Kohnke & Moorhouse, 2022). Thus, synchronous online learning allows students in separate class arrangements to participate in learning activities, together, concurrently, no matter where these students are located in the world (Tamm, 2021). Before the conception of computer networks in the 1960s, synchronous online learning was unachievable. Today, the extensive use of computer networks in education allows education institutions to reap the benefits of instant lecturer–student and student–student communication.

Due to the increased demand by individuals who attend colleges and universities, higher education institutions are compelled to include online learning modalities as part of their offerings. With the rising cost of higher education, online learning has become a cost-saving and attractive teaching modality as part of blended learning. Online learning enables the lecturer to create interactive and engaging learning environments in which students can acquire knowledge and skills (Chen et al., 2018). In these learning environments, students have flexible access to learning materials and are able to study more independently of time and place (Hudson et al., 2021). Furthermore, students are able to determine their learning content and study pace individually. The advancement of new technologies for online learning has increased ubiquitous access, ease of use, functionality, and flexibility. These technologies allow lecturers to collect data, give feedback, evaluate student progress more efficiently and adjust courses to students' needs to a greater extent (Hudson et al., 2021). These new technologies also provide options for automated grading or lecturer grading of students' work (Koorsse et al., 2016). Additionally, students and lecturers are also able to interact extensively (Joksimović et al., 2015).

"The challenge for online learning is to create an environment that engages students in ways that will maintain their high involvement, interest, and commitment throughout the duration of their learning" (Guo et al., 2016, p. 279). However, this expectation is not always realised, as there are several challenges that must be considered. Students find the lack of social presence and the impersonal nature of online learning challenging and often display low participation and motivation (Wang et al., 2017). Low completion rates for online learning, the effect of poor online learning, knowledge and information fragmentation, as well as a lack of interaction and feedback while learning, is mentioned in the literature as further challenges (Zhang et al., 2022). Furthermore, lecturers often struggle to follow student progress in an OLE (Hernández-García et al., 2015). During a survey completed by 3730 Chinese students enrolled in 150 undergraduate nursing schools, the participants reported that they received too little real-time guidance and immediate feedback from their lecturers (Sun et al., 2021). When online learning was compared to face-to-face learning for these students, 34.2% of the students were of the opinion that the discussion and guidance were not deep enough.

2.5 Digital learning platforms

A myriad of digital learning platforms has been developed worldwide over the years as solutions to the needs of students, lecturers and learning institutions. A digital learning platform is an online space or portal where educational content and resources can be created, stored, managed, and accessed, regardless of the physical location of lecturers and students (Broadbent & Poon, 2015; Goodwin et al., 2022; Su et al., 2022). These platforms accommodate resources such as live or pre-recorded lectures, slideshow presentations, exercises, assignments, assessments, and tools for collaboration between lecturers and peers. Most platforms have a monitoring component, where lecturers can analyse their students' activities, progress, and performance. Students are also able to track their progress on the platform (Broadbent & Poon, 2015).

Digital learning platforms are available in a variety of different configurations. Many universities provide learning management systems as a centralised access point to learning materials, and for lecturing staff to manage and monitor student progress. Recent developments in learning management system software include the integration of sophisticated technologies, such as artificial intelligence (AI) and extended reality technologies (Eon Reality, 2022; Turner & DeMuro, 2022). More recently, the growing complexity of learning facilitation requirements has prompted an evolution of learning management systems into ecosystems comprising a diverse collection of software and educational tools for lecturers and students (Whitemore, 2018). Other digital learning platforms include massive open online course platforms (MOOCs), which operate independently from learning institutions (Whitemore, 2018). With the rapid growth in virtual tools, virtual learning environments have also gained popularity, and made it possible for students to engage with real-world objects in a digital space. Digital learning solution platforms, on the other hand, are websites dedicated to hosting learning material dedicated to a particular knowledge field. Table 2.1 contains a summary of different categories of online learning platforms, brief descriptions, as well as examples.

Table 2.1 *Examples of learning platforms*

Category	**Description**	**Examples**	**Sources**
Commercial learning management systems	Commercial learning management systems are used by lecturers and students at education institutions. A learning management system provides opportunities for students to engage online with learning materials that have been made available by lecturers. Lecturers can store learning material, manage student learning profiles, report student progress and grades, and provide functionalities necessary for online courses. Most of these platforms are cloud-based. Learning management systems are either proprietary or freely accessible. Freely accessible or open-source platforms are typically free of charge and can be customised.	Proprietary: Blackboard Brightspace Canvas Open-source: Moodle Sakai	Anthology (2022); Broadbent and Poon (2015); D2L (2022); Dalton and Turner (2021); Instructure (2022); Moodle (2022); Sakai (2022); Whitemore (2018)
Custom-built learning management systems	Custom-built learning management systems are similar in functionality to their commercial counterparts, but usually include specific custom-built functions, "tailored" for specific requirements, such as the learning platform for a business school, for example, HBX.	HBX (Harvard Business School, a custom platform) ScienceSoft	Harvard Business School (2022); ScienceSoft (2022); Whitemore (2018)
Learning experience platform	Learning experience platforms, also referred to as new age or new generation learning management systems, are optimised by using AI and data analytics to provide personalised learning geared towards the user's needs. These learning management systems are more diverse and robust than their commercial counterparts and are generally employed for enterprise training.	EdCast Docebo SAP Litmos Microsoft Viva	Cornerstone (2022); Docebo, (2021); Microsoft (2022); SAP Litmos (2022); Turner and DeMuro (2022); Whitemore, (2018)

Virtual learning environment	Virtual learning environments are designed and developed to create a collaborative virtual environment where laboratory experiences can be experienced virtually by students. Learning takes place with the help of augmented reality, virtual reality and 3D technologies, such as holograms. This relatively new type of learning environment provides learners with the opportunity to experience and understand complex objects and operations during practical laboratory sessions.	EON-XR Unimersiv	Eon Reality (2022); Mystakidis et al. (2021); Unimersiv (2019)
Learning management ecosystem	Learning management ecosystems are complex learning environments, which include a learning management system, course authoring software, tools for evaluation, learning engines that adapt in difficulty according to the level of students' skills, electronic commerce websites, and solutions for managing learning content that are integrated and presented to the student as a single solution. These ecosystems are often built with a customised front-end, creating the illusion of a single system.	NeXus (University of Notre Dame)	University of Notre Dame (2022); Whitemore (2018)
MOOC	MOOCs are independent websites of online courses that are accessible to students via the internet. These platforms host a variety of course materials, such as reading materials, recordings of lectures and problem sets, and interactive tools such as forums or social media integrations to support interaction between members of the MOOC community.	Udacity Udemy Coursera Open edX CodeCademy	CodeCademy (2022); Coursera (2022; Siemens et al., 2015; The Center for Reimagining Learning, 2022; Udacity, 2022; Whitemore, 2018)
Interactive online learning environment	Interactive OLEs or simulated OLEs are digital platforms that support interactive activities, also known as "interactivities". These platforms provide interactive exercises and simulations of realistic events and assessments and automated grading tools. The content available on these platforms are often curriculum driven or mapped to a textbook resource. These platforms are available as standalone websites, or integrations with learning management systems. Some of these platforms are licence bound, while others are free.	Licence bound: Skills Assessment Manager AM MyLab IT SimNet WileyPlus Free source: Khan Academy	Cengage (2022); Khan Academy (2022); McGraw Hill (2022); Nagel (2011); Pearson (2022); Wiley & Sons, (2022)

2.6 Theoretical foundation of the study

2.6.1 Introduction

The advancement of information and communication technology and the rapid proliferation of internet and web technology have transformed approaches to education by higher education institutions. OLEs have become a pervasive learning modality in these institutions, worldwide (Feldman-Maggor et al., 2022; Suzianti & Paramadini, 2021). Even prior to the COVID-19 pandemic, rapid growth and high adoption of education technology had been noted, with the investment in the global educational technology market reaching upwards of 18 billion US dollars in value in 2019 alone, as well as a prediction that the overall online education market will reach 350 billion US dollar by 2025 (Li & Lalani, 2020).

The portable and flexible nature of online learning, and the reduction in time and space constraints allow broader access for students to gain knowledge (Choudhury & Khataniar, 2018). Online learning has also made the interaction between students and lecturers easier and more efficient (Aparicio et al., 2017). Furthermore, the implementation of online learning assists education institutions to reduce costs, by increasing the availability of education. However, the implementation of online learning requires lecturers to be skilled in the use of these newer educational technologies; lecturers are also responsible for effectively integrating the technologies into their teaching approach in a meaningful way (Ceresia, 2016; Rodríguez-Ardura & Meseguer-Artola, 2016).

Online education is not without its challenges. Some of these challenges include the apparent lack of opportunities for face-to-face and real-time interaction with peers and lecturers (Turk et al., 2022). Serious concerns have also emerged concerning the quality of online courses and programmes. More pressing challenges are reduced persistence of engagement with an online course or programme, and the increased likelihood of students dropping out of a course compared to traditional residential students (Dai et al., 2020; Guo et al., 2016). Student disengagement with one online course in a programme could have implications for the next online course they participate in, which could culminate in students dropping out of a programme (Saqr & López-Pernas, 2021). Several factors have been identified that affect persistence of use and successful implementation of online learning. Students' engagement with course content, their ability to self-regulate their learning processes, the overall design of the course content, and the methods used to support interaction between students and lecturers have been identified as prominent factors (Kizilcec et al., 2017). In addition, the initial acceptance of an OLE is an essential first step towards achieving learning success with an OLE; however, continued engagement with the OLE is crucial to ensure actual success (Lee, 2010). With the ever-expanding internet and continued advancements in digital education, and as the demand for the implementation of such systems increases, higher education institutions are experiencing increased pressure to understand the underlying mechanisms of the interactive features of online learning (Rodríguez-Ardura & Meseguer-Artola, 2016).

Student academic success after using online learning is a multifaceted concept and is characterised by student behaviours and the OLE. The learning environment, content, pace, sequence, and learning style significantly contribute to student performance and success with an OLE (Aparicio et al., 2017). Learning is a long-term process in which the results can only be measured after a significant investment of time and effort. Students' ability to sustain attentiveness and remain intensely productive over time vary greatly between individuals. The online engagement of a group of 106 students at Qassim University was assessed using hidden Markov models during a three-year longitudinal study. It was uncovered that 28% of the students in this group were not engaged, 33% of students had an intermediate level of engagement, and only 33% of students displayed a high level of engagement (Saqr & López-Pernas, 2021).

The success of online learning technologies has been studied in different ways. Because online learning technologies belong to the broad category of information systems, most studies are described in terms of information systems. In the 1980s, the successful implementation of information systems was studied in terms of functionality, by focusing on the technical components of the information systems (Rockart, 1982). Initially, the success of information systems was measured in terms of system quality, system usage, user behaviour, and satisfaction (Aparicio et al., 2017). After that, information systems success was studied in terms of systems quality, information quality, service quality, user satisfaction, and perceived user benefits (DeLone & McLean, 1992; DeLone & McLean, 2003). Today, the eventual successful use of information systems is studied in terms of its initial adoption and, subsequently, continued engagement with the technologies (Chiu et al., 2005). Bhattacherjee (2001) and Limayem and Cheung (2011) stress that information system adoption constitutes only the first step towards overall information systems success, and that continued use (also referred to as continuance) of information systems technology is vital to ensure successful information systems implementation.

2.6.2 Adoption of technology

In the study of information systems technology adoption, several theoretical models have been applied. Information systems research has been based on intention-based models taken from social psychology, with the aim of determining influencing factors (Davis, 1989). Research over the past two decades has focused mainly on behavioural models, including the theory of reasoned action, the theory of planned behaviour, and the technology acceptance model (TAM) and its variants (Limayem et al., 2003). TAM, which describes a user's willingness, or intention, to accept the technology, is one of the most widely applied models in the study of technology acceptance (Davis, 1993). TAM has been applied extensively to the study of a user's acceptance of various technologies, including OLEs, the World Wide Web, wearable healthcare technologies and autonomous vehicle technologies (H. Cho et al., 2020; Gefen & Straub, 2003; Lu et al., 2009; Mohammadi, 2015; Moon & Kim, 2001; Nastjuk et al., 2020). The factors that have been found to have a positive influence on the behaviour of a user's intentions are perceived usefulness, perceived ease of use, perceived credibility, self-efficacy, and financial resources (Wang et al., 2006).

Perceived usefulness and perceived ease of use are viewed as the central variables of the TAM and are also applicable to OLEs. Both perceived usefulness and perceived ease of use are affected by external factors and impact an individual's attitudes – negative or positive – towards the use of technology (C. Chang et al., 2017). According to Davis (1989), perceived usefulness is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance”. Perceived usefulness variables have been tested for different types of technologies and systems, among which wearable devices (Chuah et al., 2016), autonomous vehicles (Xiao & Goulias, 2022) and smart farming technologies (Caffaro et al., 2020). These studies showed that, if a user finds that technology is useful, the user will be inclined to use the technology (Mahfuz & Saha, 2015). Moreover, studies have consistently shown that perceived usefulness is an important factor in the intention to adopt technology (Abdullah et al., 2016; Davis et al., 1989; Segars & Grover, 1993; Taylor & Todd, 1995; Venkatesh, 2000).

The perceived ease of use variable relates to an individual's assessment of the effort involved in using technology. Davis (1989) describes perceived ease of use as “the degree to which a person believes that using a particular system would be free of the effort”. Several studies have shown the importance of perceived ease of use of technology, for example, in electronic commerce (Renny et al., 2013; Sun et al., 2009), mobile commerce (Chi, 2018; Henderson & Divett, 2003), mobile banking (Malaquias & Silva, 2020; Wang et al., 2006). These studies report a positive effect of perceived ease of use of the technology on the behavioural intention to use the specific technology. Thus, when a user finds a system easy to use, the user will be inclined to use the system (Al-Ajam & Md Nor, 2013).

Scholars in education have modified the TAM to include various external factors in the study of technology acceptance in learning with digital technology. Over the years, the TAM has proven to be a robust model for technology adoption in e-learning (King & He, 2006; Taherdoost, 2018). The TAM has been used to establish which factors could influence a student to decide to use a new learning environment; these factors include computer self-efficacy, social influence, perceived enjoyment, computer anxiety and experience (Chang et al., 2017). In particular, the factors perceived usefulness and perceived ease of use play a major role in technology adoption in e-learning. These factors are influenced by factors from external sources and impact negatively or positively the attitudes of an individual toward technology. Alsabawy et al. (2016) state that perceived usefulness is a major proponent in the measurement of a user's acceptance and the ultimate success of the implementation of an e-learning technology, although a lack of evidence exists to support the effect of information technology infrastructure services on the usefulness of the learning system. A study was conducted amongst randomly selected universities/colleges in the region of Northeast India to examine faculty members' perception and adoption of an e-learning platform for academic purposes (Choudhury & Khataniar, 2018). Data were collected from 81 faculty members through a questionnaire. The study found that the adoption and use of the e-learning platform depended mainly on behavioural intentions and attitudes towards using the platform. Perceived usefulness and job relevance were the strongest predictors of behavioural intention and attitudes towards the platform.

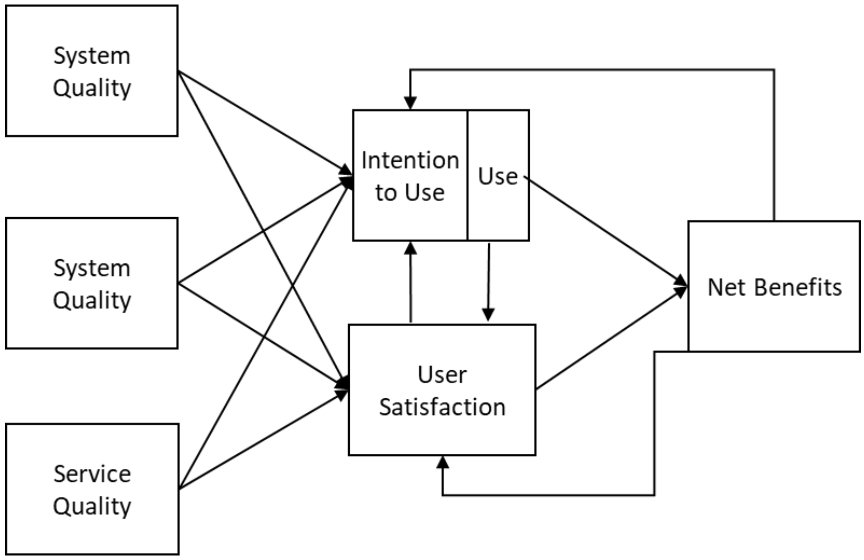
2.6.3 Continued engagement with information systems

Research about the intention to continually use information systems technology in education is a recent trend. The realisation that long-term enjoyment when engaging with information systems is as important as the adoption of the technology has become one of the major drivers in research into the intention to continuously use an information system (Daǂhan & Akkoyunlu, 2016). The phenomenon of continued use of an information system has been described using several phrases interchangeably: continuance, continuous use intention, continuance intention, intention to continue using, continuance use intention, and continuance usage intention. Once users adopt an information system, their continued engagement stems from the motivations behind their decisions to continue using the information system (Ambalov, 2018). Different learning environments play a major role in the behaviour of a user of an information system (Bhattacherjee, 2001). The intention to continue using an information system refers to users' "intention to continue using an IS after its initial acceptance" (Bhattacherjee, 2001). Thus, the success of an information system depends on users continuing to engage with the system, rather than on the acceptance of the technology, because once users start engaging with a system, psychological motivations, which affect their decisions to continue engaging, will emerge. When studying the intention to continuously engage with an information system, factors are identified that explain why individuals use technology for a long time and continue using the technology (Lin et al., 2017). Thus, researchers depend on general information systems usage behaviour theories to identify factors that may explain the continued use of a system. To study continued information systems usage in e-learning, several theories/models have been applied to understand the phenomenon of e-learning intention to continuously engage.

2.6.3.1 IS success model

One of the most tested models in the study of information systems success is the information systems success model. DeLone and McLean proposed the information system success model in 1992 (DeLone & McLean, 1992). Although this model initially proposed studying organisational effectiveness in economical environments, it has been applied to estimate success, usage and continuance of many learning systems in the educational context (Daɫhan & Akkoyunlu, 2016). This model provides a theoretical basis for linking e-learning systems with students' continued engagement and successful learning outcomes (Chen, 2010). In Dağhan and Akkoyunlu's model (2016), variables are used to estimate information systems success under different conditions. Initially, system quality and information quality were found to affect the use variable and user satisfaction variable, both singularly and jointly (Ramayah et al., 2010). Later, Seddon (1997) added to the model the variable perceived usefulness, as a determinant of user satisfaction, and a few years later, Rai et al. (2002) extended the model by adding information quality as the antecedent of satisfaction. In 2003, DeLone and McLean revised the model to include service quality as a variable(DeLone & Mclean, 2003). This model became more dynamic with the addition of other variables, in addition to satisfaction and usage (Daɫhan & Akkoyunlu, 2016). For example, variables such as system quality, information quality, use, user satisfaction, individual impact, and organisational impact have been studied in relation to information systems success (Cidral et al., 2018). In information systems success research, the factors related to user or social characteristics represent the model's independent variables, and factors related to technology concepts, such as information systems usage, the user's satisfaction or net benefits, represent the model's dependent variables (Daɫhan & Akkoyunlu, 2016). In a large study, continued usage as a measure of information systems success was analysed using a structured questionnaire that was completed by 1616 undergraduate and postgraduate students at public universities in Malaysia (Ramayah et al., 2010). The outcome of this study indicated that factors such as service quality ($\beta = 0.382$, $p < 0.01$), information quality ($\beta = 0.338$, $p < 0.01$) and system quality ($\beta = 0.175$, $p < 0.01$) positively related to the intention of postgraduate students to continue using the university's information system, which explained a total of 59.1% of variance. In terms of the predictive power of these factors, service quality had the greatest influence on the students' intention to continue using the university's information system, followed by information quality and system quality.

Figure 2.1 *Information systems success model depicting variables that predict net benefits of information systems success*



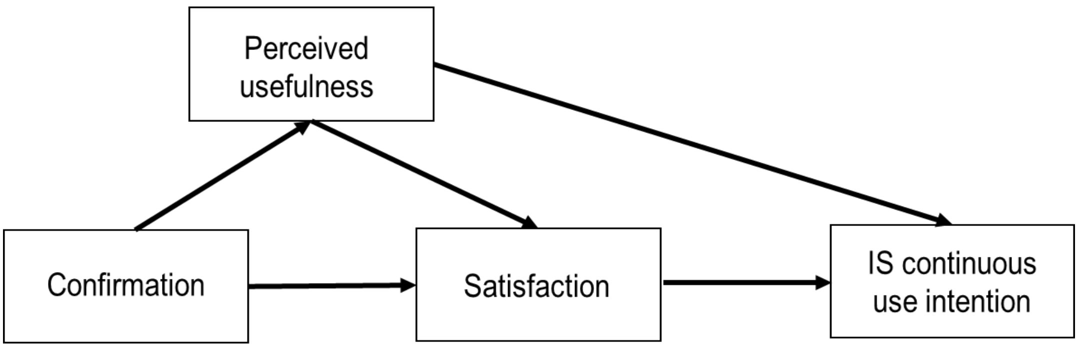
Source: DeLone and Mclean (2003)

2.6.3.2 Expectation-confirmation model

One of the first models used to explain continued information systems usage in e-learning was the expectation-confirmation model (ECM). The ECM is based on the expectation-confirmation theory of Oliver (1980), who proposed the ECM to evaluate consumers' satisfaction and post-purchase behaviour in the study of consumer behaviour (Figure 2.2). Because e-learning involves information systems technology via the internet, the ECM has been applied extensively to assessing information systems continuance in the e-learning context (Chang & Zhu, 2012). Bhattacherjee (2001) adapted this initial model and included post-consumption expectation, which is represented in the model by post-consumption perceived usefulness. This model theorises that a user's intention to continue using an information system is dependent on the variables, the user's level of satisfaction with the information system; the extent of users' confirmation of expectations; and postadoption expectations, in the form of perceived usefulness (Chang & Zhu, 2012). The ECM was expanded in 2006 beyond its instrumental focus (Thong et al., 2006). This expanded ECM incorporated the post-adoption beliefs of perceived usefulness, perceived enjoyment, and perceived ease of use. The variable perceived usefulness was drawn from the TAM (Davis, 1989). This expanded model was empirically validated with data obtained by surveying 811 active mobile internet service users. The outcome of this study revealed that 57.6% of the variance in continued information system usage intention could be explained by its influencing factors, and that 67.8% of the variance in satisfaction was explained by its influencing factors. It can, thus, be concluded that the expanded ECM can provide supplementary information that is relevant to understanding continued information system usage. The ECM, as well as its expanded version, indicate that users' continued engagement with an information system is determined by their satisfaction with the information system and perceived usefulness of continued use (Chang & Zhu, 2012). Their satisfaction, in turn, is influenced by the perceived usefulness and confirmation of expectation from prior use of the information system, while post-acceptance perceived usefulness is influenced by users' confirmation level.

A study on the continuance usage of internet-based learning technologies (Limayem & Cheung, 2008) integrated a habit variable into the ECM and tested the extended model on 303 students. They found that habit, continuance intention, satisfaction and prior behaviour were variables that could affect the intention to continue to use of internet-based learning technologies. In this study, the predicted variance in continuance usage was 23%. The ECM has been extensively tested in information systems research, which confirms that the model is useful for explaining the persisted use of an information system (Wang et al., 2019).

Figure 2.2 *Expectation-confirmation model depicting factors that influence IS continuous use intention*



Source: (Thong et al., 2006)

Several studies have combined the ECM with other models. In one of the early studies, ECM was integrated with the theory of planned behaviour model (Liao et al., 2007). This study found that the intended continued use of online systems is determined by satisfaction, perceived usefulness, and subjective norms. The findings of this study brought about further changes to the ECM, in which the impact of subjective norms on continuance use intention became a consideration (Terzis et al., 2013). The ECM was also combined with the TTF (task-technology fit) model in a study of e-learning (Larsen et al., 2009). The variables added from TTF were task-technology fit and utilisation. In this study, data were gathered from university college teachers about information system continued use intention. Structural equation modelling of the data reveals that variables from TTF, as well as variables from ECM, explained users' information system continued use intention.

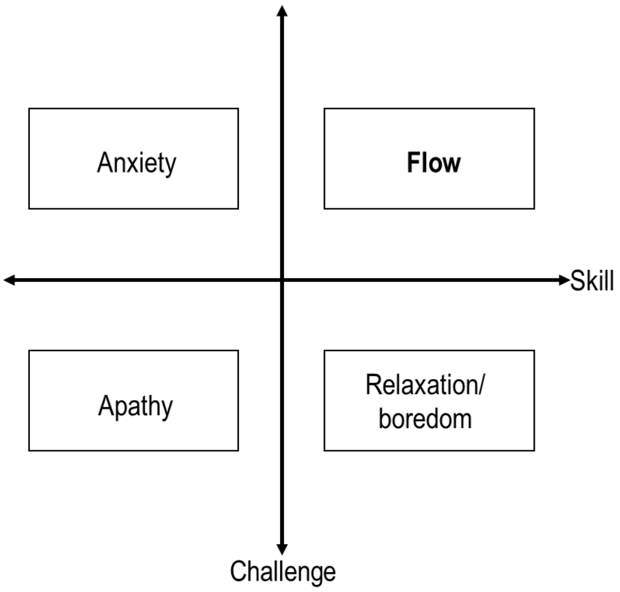
The ECM has been applied in many different contexts. For instance, the continued use of cross-channel instant messaging has been assessed with an integrated version of ECM with the process virtualisation theory. The variables of the sensory dimensions of communication, synchronism, relationship, identification and control were added as additional variables (Li et al., 2009). In a more recent context, continued engagement behaviour was studied in microblogging services, virtual worlds, and social networking sites. The study found that a user's intention to maintain engagement with the app Twitter was influenced mostly by three factors, perceived usefulness, satisfaction, and habit (Barnes & Böhringer, 2011).

2.6.3.3 Flow experience model

The flow experience theory is inherently related to learning. When a student embarks on learning a new skill, the challenge may be overwhelming when a student's beginning level of ability is exceeded (Shernoff & Csikszentmihalyi, 2009). The flow experience model developed by Csikszentmihalyi (1990) provides a heightened understanding of the experience of deep engagement, as well as the factors that may promote it (Schmidt, 2010). Csikszentmihalyi (1990) describes an optimal flow experience as taking place when an individual reaches a state of heightened concentration, involvement awareness, attentive focus, accomplishment, and control while taking part in an activity and also finding joy from the process of completing the activity without a guaranteed reward at the end, while losing track of time (Schmidt et al., 2014). To enter this state of flow, the skill level of the individual should increase to correspond with the level of the challenge, which may require both mental and physical exertion (Shernoff & Csikszentmihalyi, 2009).

The conditions in which an individual derives a flow experience may vary widely. Even though the tasks that individuals perform may differ extensively, there are a few phenomenological conditions that can be attributed to an optimal flow experience (Csikszentmihalyi, 1990). The conditions that could promote optimal flow is creating a task or environment which requires engagement in an activity for its own sake with the presence of clear goals, a balance between task difficulty and the skillset of the individual, devoid of distractions with reliable instant feedback mechanisms. A flow experience is likely to ensue when challenges and skills are relatively high and in balance (Csikszentmihalyi, 1990). The flow model is often shown as a chart showing four channels of experience, which are each defined by the relative relationship between challenge and skill (Schmidt, 2010). When challenges and skills are both high, individuals tend to experience flow (Figure 2.3).

Figure 2.3 *Flow model depicts the four channels of experience*



Source: (Schmidt, 2010)

In studies of information systems, continued engagement, too, has an optimal flow experience been proven to be important. Flow experience has been widely tested in online environments, for example, banking (Lee & Tsai, 2010), instant messaging (Zhou & Lu, 2011), online games (Choi & Kim, 2004), as well as e-learning (Lee, 2010). These studies found that a flow experience is an essential factor in an individual's behaviour when engaging with an information system (Chang & Zhu, 2012). An optimal flow experience is of particular interest in an individual's feeling of satisfaction when engaging with an information system.

2.6.3.4 Cognitive model

The cognitive model was developed by Oliver in 1980. This model is regarded as the foundation for other models and theories used to study information system continuous use intention (Dałhan & Akkoyunlu, 2016). This model posits that the variable confirmation behaviour influences the user's satisfaction with an information system in general and that satisfaction with the information system in turn influences the long-term intention to use an information system. The satisfaction implicates a judgment-based performance component of the model, and variable attitude implicates a general assessment of the technology usage of a user. The inclusion of the variables satisfaction and attitude that affect the general day-to-day usage and long-term usage, makes this model as important as the later models.

2.6.3.5 Technology continuance model

The technology continuance model is an integrated model of three other models. The technology continuance model was created by combining the TAM, ECM and cognitive models, and is used to predict long-term usage of information systems (Liao et al., 2009). After testing the three models, the TCM was developed by using the six variables: confirmation, satisfaction, perceived usefulness, perceived ease of use, attitude and information system continuance intention. The major contribution of the technology continuance model is the combination of the two variables, attitude and satisfaction, into one continuous use model. This model can be applied to study users at different stages of the technology cycle, for example, initial, short-term, and long-term users.

2.6.4 Assessment of information system continuous use intention

In social sciences research, statistical analysis tools have been used for many years to explore and confirm research findings. During the 1980s, first-generation statistical methods, such as factor analysis and regression analysis, dominated the research; however, from the 1990s, the use of second-generation methods increased rapidly (Hair et al., 2017). Exploratory first-generation techniques incorporated multidimensional scaling, cluster analysis and exploratory factor analysis, while confirmatory techniques incorporated confirmatory factor analysis, multiple regression, logistic regression and analysis of variance. PLS-SEM is a widely used second-generation technique for exploratory studies. In turn, covariance-based SEM is used in confirmatory studies. PLS-SEM is primarily used to develop theories in exploratory research (Suzianti & Paramadini, 2021). In contrast, covariance-based SEM is used to confirm (or reject) theories by examining causality relationships between variables.

In social sciences research, SEM is used to test relationships between observed and latent variables. The term SEM encompasses a family of related procedures, rather than a single statistical technique (Kline, 2016). Other terms used interchangeably for SEM are covariance structure analysis, covariance structure modelling, or analysis of covariance structures. As is the case with other statistical procedures, the quality of the results depends on the validity of the researcher's ideas. The goal in a SEM project is to assess a theory by constructing a model that visually represents the predictions of that theory among possible latent variables measured with suitable, observable variables (Civelek, 2018). SEM confirms the correspondence of the data of the relationships in the theoretical model. One of the main reasons for the spread of SEM in social sciences research is its ability to measure these relationships with a single model (Civelek, 2018). Because latent variables cannot be measured directly, data are collected through the measurement of the observed variables, which are then connected to the latent variables through SEM. An additional justification for the predominant adoption of SEM is for its ability to account for and minimise measurement errors and relationships between errors in the observed variables. Other reasons for the adoption of SEM are that relationships amongst hidden structures that are not directly measured can be revealed; it takes into consideration possible inaccuracies in the measurement of the observed variables, and it allows for the analysis of models with varying amounts of complexity and reveal direct and indirect relationships between variables (Civelek, 2018).

SEM is a graphical modelling methodology. The main feature of SEM is the clear distinction between observed variables and latent variables. At one level, the relationships are represented in both graphical and equational form. Data are collected for the observed variables, which can be categorical or continuous in nature. In contrast, in SEM, all latent variables are continuous (Kline, 2016) The latent variables in SEM relate to hypothetical variables, or explanatory concepts that reflect a continuum that cannot be measured directly. Latent variables can represent a wide range of phenomena. In this study, the phenomenon information system continuous use intention is a complex variable comprising many dimensions. The data obtained through the measurement of the observed variables are used as indirect measures of the latent variable.

A variety of software applications exist that can be used for SEM studies. The most commonly used programs are LISREL (Linear Structural Relations), AMOS (Analysis of Moment Structures), MPlus, and EQS (Equation Modelling Software), which are all standalone software applications that do not require more processing power than what is offered by a standard office computer (Civelek, 2018; Hair et al., 2017; Kline, 2016). Several free computer programs are also available for SEM. These include Ωnyx, a graphical environment for creating and testing SEMs, and various SEM packages, such as lavaan or

SEM for R (Kline, 2016). With the increasingly visible application of PLS-SEM in the social sciences disciplines, the program SmartPLS has become popular in recent times (Hair et al., 2017). The use of SmartPLS will be discussed in Chapter 3.

2.7 Summary

Online learning has become ubiquitous in learning configurations at universities. Lecturers are now in the position to select from a wide range of information systems, of which some are highly sophisticated and make use of AI, and others comprise collections of software programs making up ecosystems. Because students are from diverse backgrounds, have varied levels of skills, and display different approaches and behaviours towards online learning, their success with online learning may vary extensively. A student's successful use of an information system in OLE depends on many factors, some of which are known and others unknown. One of the major concerns of university lecturers is the high drop-out rates of students studying in OLEs. Thus, lecturers continually seek to understand which factors influence a student's continued engagement with an information system. This structural equation modelling project was, thus, undertaken to identify factors that may influence a student's intention to continuously engage with the skills assessment manager OLE to study basic digital literacy.

Chapter 3

Project conceptualisation and methodology

3.1 Introduction

Every first-year student enrolled at the CUT, regardless of the type of qualification enrolled for, is introduced to a digital literacy module. More than 2000 first-year students in all four faculties register for the module Basic Digital Literacy every year. The purpose of this module is to provide students with a basic understanding of computers and Microsoft Office productivity applications. An understanding of computers and productivity software applications contributes to students' personal and academic success and ensures their successful participation in the technology-driven workplace once they graduate (Brown et al., 2020; Gibbs et al., 2014; Koorsse et al., 2016; Udeogalanya, 2022). To help lecturers manage, teach, assess, and monitor such a large group of students, this module is delivered through an OLE. However, it is known that student engagement with OLEs is tenuous (Alkhaldi & Abualkishik, 2019; Roca et al., 2006; Spector & David, et al., 2014; Venter & Swart, 2018; Yan et al., 2021). Thus, identifying and understanding the factors that influence students' intention to continuously engage with an OLE while learning in the module Basic Digital Literacy, informs decisions to optimise the OLE to maximise student learning success. This project was, therefore, undertaken to identify factors that could predict first-year students' intention to continuously use the OLE used for the Basic Digital Literacy module. The main research question that underpinned this study is:

> *Which factors influence students' intention to continuously use the OLE for Basic Digital Literacy at the CUT?*

In order to determine the factors that could influence students' intention to continuously use the OLE of Basic Digital Literacy, a PLS-SEM approach was followed. PLS-SEM is generally used in research where there is a need to predict a set of dependent variables within a large set of independent variables (Abdi, 2007). SEM is a multivariate statistical technique that allows for the estimation and testing of causal relationships between variables (Hair et al., 2017). This statistical technique examines the combined effect of one or more independent variables on dependent variables arranged in a path diagram and is, thus, broadly referred to as path analysis. The variables in a SEM path analysis are distinguished according to their measurement role in the model. There are two main variable types, latent and observed variables. Latent variables are unobservable, while observed variables are measurable. Table 3.1 provides further details and synonyms for the different types of variables used in PLS-SEM.

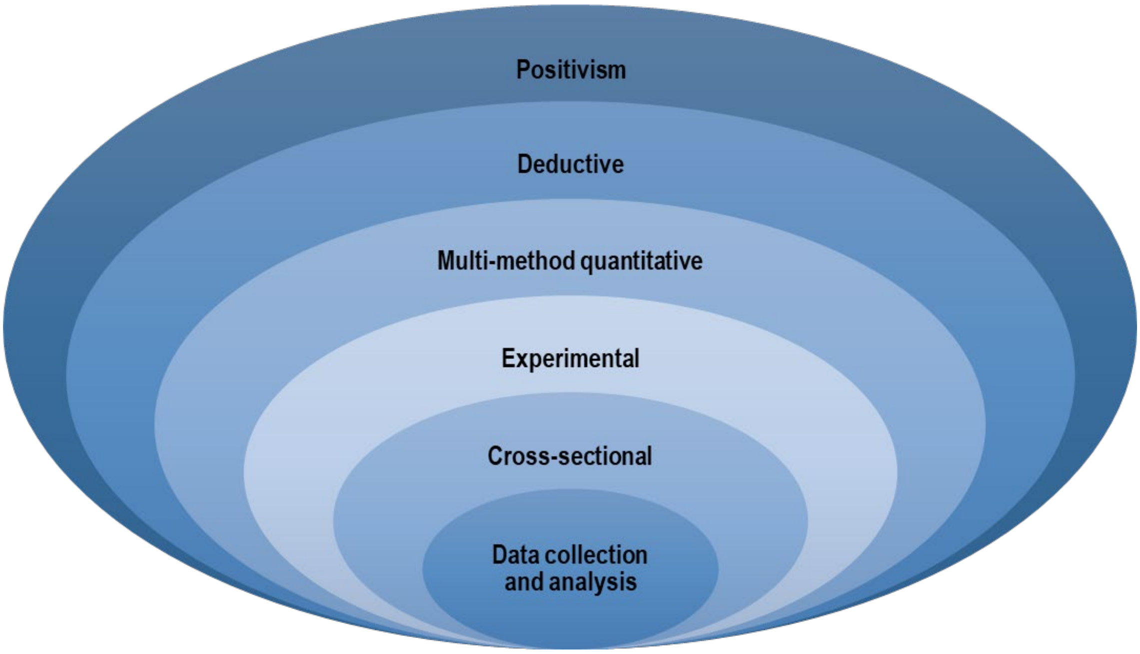
Table 3.1 *Descriptions and terminology of variable role in a SEM path analysis*

Variable	Description	Synonym
Latent	Latent variables are unobservable variables arranged in a path diagram depicting potential causal relationships.	Factors, concepts, conceptual variables
Observed	Observed variables are used to measure latent variables.	Indicators, inputs, measures

3.2 Study approach

In this study, the philosophical underpinning was that of a positivist viewpoint. The positivist philosophical viewpoint originated from the natural sciences and is characterised by testing hypotheses developed from existing theory (Crotty, 1998). A positivist researcher attempts to undertake a research process in a value-free manner, as far as possible. In this project, theories from information systems and cognitive behavioural psychology were used to formulate hypotheses that were tested. Deductive reasoning was applied, in which a sequential multi-method approach was followed to gather and analyse quantitative data. The study design can be described as peeling the layers of the research onion (Saunders et al., 2015; Saunders et al., 2019) (Figure 3.1).

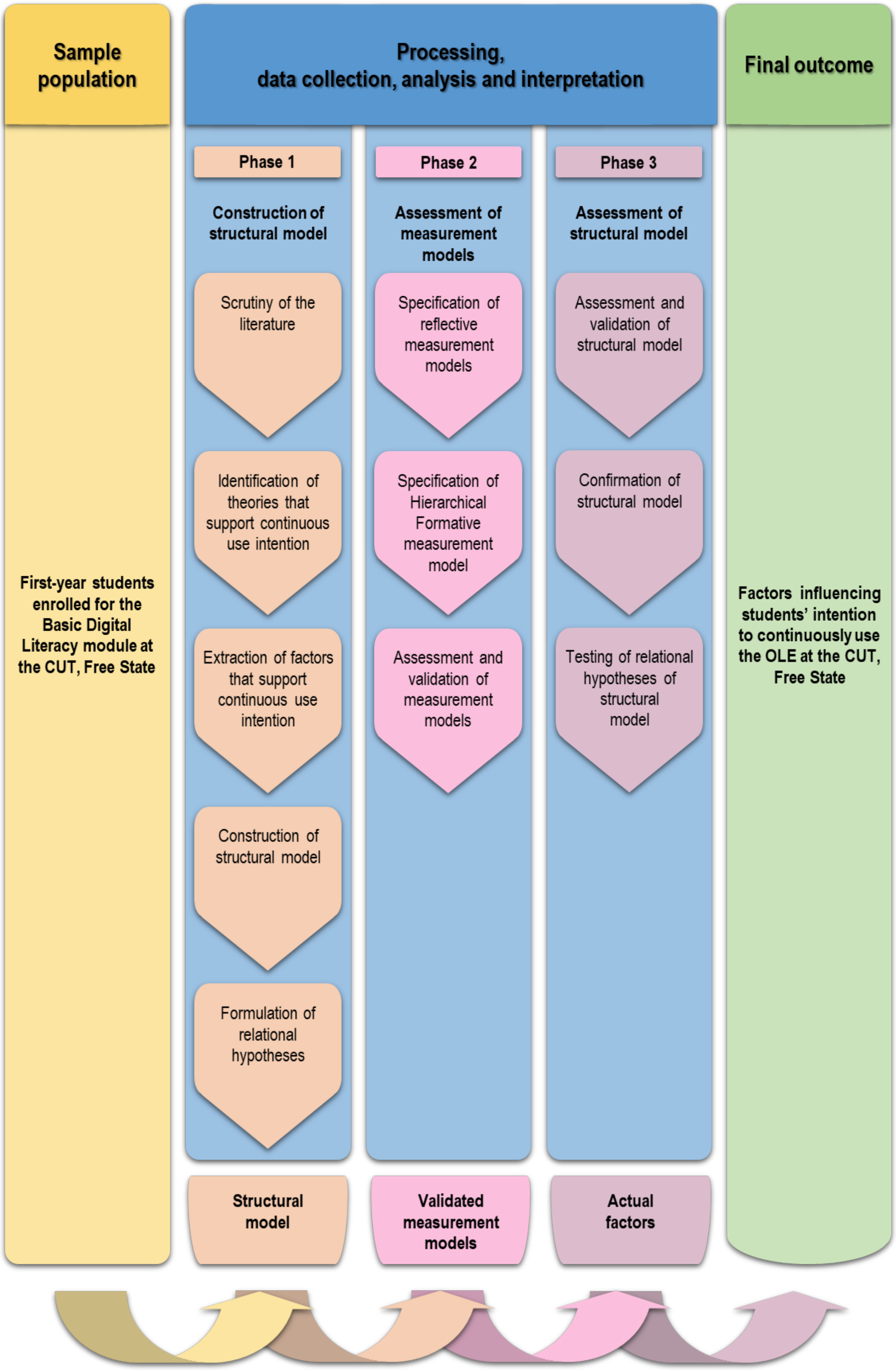
Figure 3.1 *Research onion depicting the research philosophies and methodological approaches followed in this study*



3.3 Conceptual framework

The study was undertaken in three phases. In Phase 1, a literature search was undertaken to identify relevant literature and theories. Factors (latent variables) that had the potential to influence students' intention to continuously use the Basic Digital Literacy OLE were identified and extracted from the literature. These factors were used to construct a path diagram, referred to as a structural model. This structural model indicated linkages between the factors that could play a role in students' intention to continuously use the OLE. These factors were, thus, named potential factors, while the factor representing the students' intention to continuously use the OLE was referred to as the target factor. The structural model, containing potential factors and the target factor, were then used to formulate the relational hypotheses that were tested in this study. In Phase 2, the potential factors and the target factor were operationalised by specifying observable variables in several measurement models, which were assessed for their reliability and validity. In Phase 3, the structural model was validated and assessed, and the relational hypotheses tested. After testing the hypotheses, the actual factors that influence students' intention to continuously use the Basic Digital Literacy OLE could be identified amongst the potential factors. Figure *3.2* presents a conceptual framework illustrating the major components of the three phases of the study.

Figure 3.2 *Conceptual framework that underpinned the study*



The research process of the project was guided by a series of research sub-questions that addressed the main aim of the study and was accompanied by several objectives. For each of the three phases, a single research sub-question was composed. The objectives associated with each question indicate what actions were required to accomplish the aim of the study. Table 3.2 depicts the three research sub-questions that were addressed during the research process and the objectives that were pursued to determine which actual factors influenced students' intention to continuously use the Basic Digital Literacy OLE. The table also indicates in which chapters the achievement of the objectives will be reported.

Table 3.2 *Summary of the research sub-questions and objectives*

Research sub-question	Objective	Chapter
1. Which theories and potential factors can be used to construct a structural model containing potential factors that influence students' intention to continuously use the SAM OLE??	1. To conduct a literature review to identify relevant theories and potential factors that will aid in the identification of actual factors that could contribute to the prediction of students' intention to continuously use the OLE. 2. To construct a structural model depicting the potential factors that could contribute to the prediction of students' intention to continuously use the OLE. 3. To derive relevant relational hypotheses between potential factors and the target factor of the structural model.	4
2. Which indicators of the measurement models can be used to measure the potential factors that influence students' intention to continuously use the SAM OLE?	4. To determine which of the potential factors will be measured with reflective or formative indicators. 5. To devise a measurement instrument containing reflective and formative indicators to measure the potential factors and the target factor. 6. To administer the measurement instrument to obtain measurements of the potential factors and the target factor. 7. To use the measurements of the potential factors and the target factor to determine the validity and reliability of the measurement models.	5
3. Which of the potential factors are actual factors that influence a students' intention to continuously use the SAM OLE?	8. To determine the collinearity amongst the potential factors and the target factor. 9. To identify the Actual factors that predict students' intention to continuously use the OLE.	6

3.4 Study population

At the CUT, all the first-year students of the four faculties enrol for the Basic Digital Literacy service module. In this module, students learn to use the Microsoft Office productivity applications Word, Excel, PowerPoint, Outlook, and Access. More than 2000 students enrol for the module on both campuses of the CUT, in Bloemfontein and Welkom. For this study, the students enrolled at the Bloemfontein campus were asked to participate voluntarily. Initially, 1003 students completed the questionnaire; however, after applying exclusion criteria, the study population comprised 793 students who participated voluntarily.

3.5 Materials

3.5.1 Basic Digital Literacy OLE

At the CUT, the Basic Digital Literacy service module is taught following a blended mode of delivery. In addition to face-to-face delivery, the online learning component of this module is delivered through an OLE, namely, the Skills Assessment Manager (SAM) OLE developed by Cengage (2022). The SAM OLE is a web-based interactive online learning environment that was developed to equip students with Microsoft Office and computer skills. The SAM OLE facilitates students with hands-on practise, to build skills in a visual and interactive interface. Students can observe, practise, and apply the skills they have obtained live in the learning environment of the different Microsoft Office applications. The SAM OLE also provides assignments, so that students can develop skills, and assessments to monitor student progress.

3.5.2 Data capturing and processing software

Several software applications were used in the different phases of the project to gather, prepare, and analyse data. To gather data to identify the factors that influence students' intention to continuously use the SAM OLE, questionnaires were distributed using the web-based software QuestionPro (2022).[1] QuestionPro, created and developed by, Vivek Bharkashan, comprises an assistive interface that allows for questionnaire design for creating survey questions, accessing tools for distributing the surveys, as well as tools for the analysis of response data. Students obtained access to the QuestionPro questionnaire via the CUT Blackboard learning management system. The response data gathered with

[1] https://www.questionpro.com/v18/

QuestionPro was then captured and prepared for analysis using Microsoft Excel and SPSS (Statistical Package for the Social Sciences, build 1.0.0.7.8.1, developed by IBM, 2022).

3.5.3 Analytical software applications

The statistical package SPSS was used to calculate various summary statistics for the data. However, most of the analytical procedures to identify the factors that influence students' intention to continuously use the SAM OLE were performed with the software application SmartPLS, developed by Ringle et al. (2015). SmartPLS has a graphical user interface for variance-based PLS-SEM path modelling. It is a stand-alone application built on a Java Eclipse platform, making the PLS-SEM operating system independent (Monecke & Leisch, 2012a). SmartPLS was chosen for the analysis of the PLS-SEM data in this study for the following reasons:

- SmartPLS has a drag-and-drop facility to specify models using an intuitive graphical user interface.
- SmartPLS supports the analysis of complex models comprising hierarchical layers.
- SmartPLS supports the analysis of a variety of measurement models, in particular, the formative measurement model, and
- SmartPLS can be used to calculate a wide range of statistics using various procedures, including complex Bootstrapping routines.

3.6 Methods for Phase 1: Construction of the structural model

3.6.1 Identification of relevant theories and potential factors

Two steps were followed to identify relevant theories described in the literature, from which potential factors were extracted to construct a structural model. A structural model in this study is a diagram that depicts the different factors that may influence students' intention to continuously use the SAM OLE, and how they relate to one another with one-directional arrows. The potential factors and the target factor are unobservable latent variables, measured with observable variables. The observable variables are the items of a questionnaire and are referred to as indicators (Hair et al., 2017). In the first step, electronic database searches were undertaken to source relevant literature, while, in the second step, these literature sources were reviewed to identify relevant theories from which potential factors could be extracted.

In the pursuit of literature containing relevant theories, several electronic databases were searched. These electronic databases included the Association for Information Systems (AIS) eLibrary, Elsevier, Emerald Insight, IEEE Xplore, JSTOR, Multidisciplinary Digital Publishing Institute (MDPI), ResearchGate and ScienceDirect. Initially, the search terms “online learning environments”, “e-learning environments”, “OLE”, “Microsoft Office productivity applications”, “Skills Assessment Manager”, and “continuous intention” were used to search these databases, as well as combinations of these terms. After an exhaustive search using these initial terms, other search terms, synonyms and derivatives of the initial search terms, were explored. These terms were, for example, “tertiary education”, “web-based learning environments”, and “student satisfaction”. During all searches, relevant leads were also followed.

After completing the electronic database searches, the sourced literature was scrutinised for relevant theories and factors that could be used to predict students’ intention to continuously use the SAM OLE. Before the literature sources were assessed for their eligibility, duplicates were removed from the literature collection. Thereafter, exclusion and inclusion criteria were applied to identify those sources that could be used to identify relevant theories from which potential factors could be extracted for the construction of a structural model. The structural model formed the foundation for testing relational hypotheses to identify actual factors that influence students’ intention to continuously use the SAM OLE (Table 3.3).

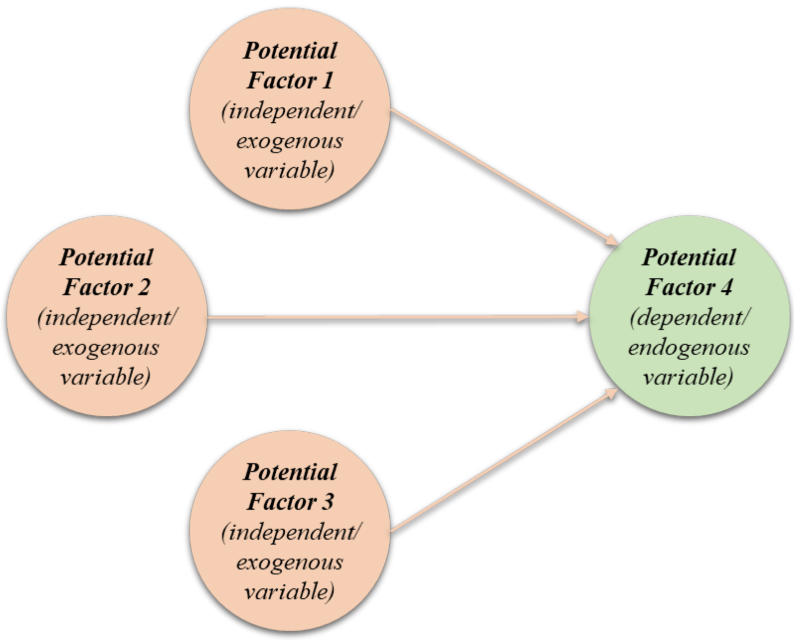
Table 3.3 *Inclusion and exclusion criteria for identification of relevant literature*

Criterion type	Criterion
Exclusion	Literature published earlier than the year 2000
	Literature published in a foreign language
Inclusion	Literature that addresses the students’ continuous use intention of an OLE
	Literature that used structural equation modelling for systematic analysis of data

3.6.2 Assembly of structural model

Once valid theories and potential factors for the prediction of students' intention to continuously use SAM OLE had been identified, a structural model was constructed. This model served as the foundation for the formulation of relational hypotheses that could be tested. The structural model, also referred to as the inner model in the context of PLS-SEM, connects the potential factors (shown as circles or ovals) to one another and also displays the relationships between the factors (shown with arrows). These factors were arranged in the model based on their relative influence on the target factor, *continuous intention*. For the construction of the structural model, a flow diagram approach was followed, reading from left to right. During the construction of the model, the target factor *continuous intention* was positioned on the far right of the model, with all other influencing potential factors placed in a logical sequence to the left of the target factor. The potential factors and the target factor were interconnected in bivariate relationships, indicated with unidirectional arrows pointing to the right, ultimately in the direction of the target factor (Figure 3.3). If a potential factor had only outward-pointing arrows, with no inward-pointing arrows, these factors are referred to as independent or exogenous potential factors. In contrast, potential factors with inward-pointing arrows are referred to as dependent or endogenous potential factors.

Figure 3.3 *Example of an excerpt of a structural model depicting the unidirectional relationship of the independent potential factors to the dependent potential factor*



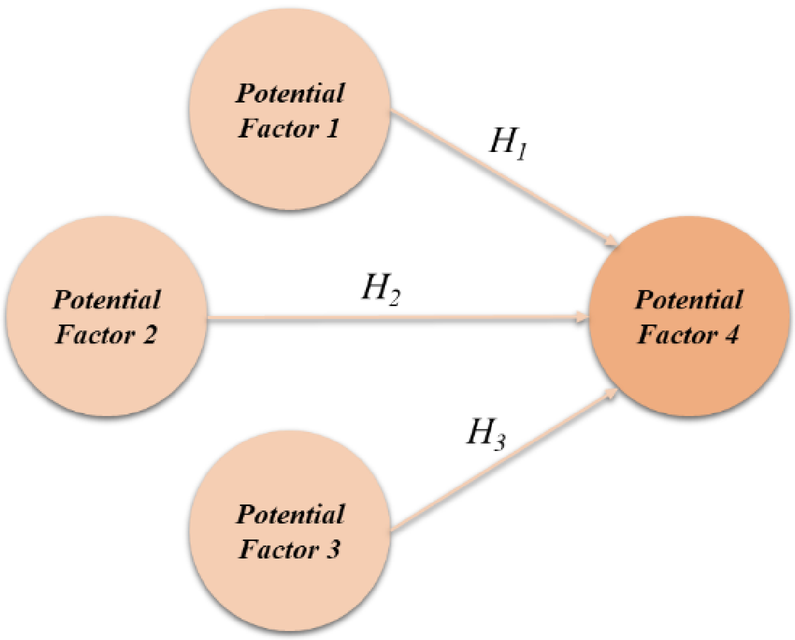
3.6.3 Formulation of relational hypotheses

The connecting arrows, as well as the direction of the arrows in the structural model, formed the foundation of the formulation of the relational hypotheses between independent potential factors and dependent potential factors. For each of the bivariate relationships in the structural model, a relational hypothesis was formulated. These hypotheses were then tested at a 5% significance level (α = 0.05) using PLS-SEM to determine which of the potential factors influenced students' intention to continuously use the SAM OLE. Because of the unidirectional nature of the relationships between the factors in the structural model, the following format was used to formulate relational hypotheses:

> *H_x: Potential factor on the left (independent variable) of the unidirectional arrow [affects/influences] the potential factor on the right (dependent variable) of the unidirectional arrow*

Figure 3.4 depicts the way the relational hypotheses relate to the potential factors in a structural model.

Figure 3.4 *Example of an excerpt of a structural model depicting relational hypotheses linking independent potential factors with a dependent potential factor*



3.7 Methods for Phase 2: Assessment of the measurement models

3.7.1 Development of measurement instrument questionnaire

Because the potential factors in the structural model were latent variables (unobservable), they were operationalised by creating (observable) measurement variables for each of the potential factors. A questionnaire, referred to as the measurement instrument questionnaire (MIQ), was developed by making use of applicable prior studies to measure these potential factors. For each potential factor, a set of questions (items) was developed. In addition to probing for information about the potential factors, the MIQ also probed for student participants' biographical and supplemental information, which included university registration information, as well as prior experience with the SAM OLE and current digital literacy skillset.

3.7.1.1 Specification of the measurement models for the potential factors

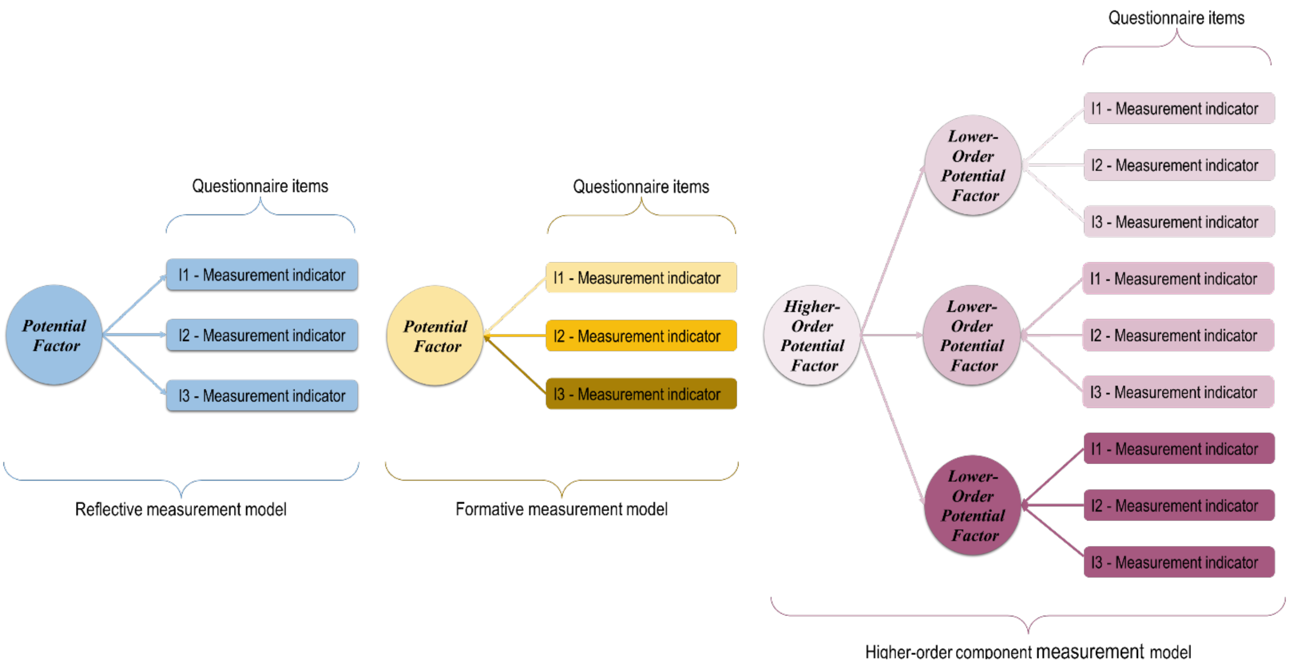
Generally, different types of measurement specifications are used to measure the potential factors of a structural model. These specifications are referred to as measurement models. Where the structural model describes the relationships between potential factors, measurement models represent the relationships between the potential factors and their items in the MIQ, which are referred to as measurement indicators. Different types of relationships exist between potential factors and their indicators. The distinction between the relationships lies mainly in the direction of causality of a relationship that exists between a potential factor and its measurement indicators (Hair et al., 2017). For this study, reflective and formative measurement models were used to measure the potential factors. In a reflective measurement model, the potential factor is assumed to cause the indicators (Hair et al., 2021). Such indicators are, therefore, also referred to as effect or reflective measurement indicators. In contrast, in the formative measurement model, the measurement indicators are specified as causes of a potential factor. The criteria specified in Table 3.4 distinguish between reflective and formative measurement model types.

Table 3.4 *Criteria used to distinguish between the reflective and formative measurement models*

Criterion	Decision	Citation
Which direction of causality exists between the indicator and potential factor?	From the potential factor to the indicators: reflective From the indicators to the construct: formative	Hair et al. (2017); Raykov and Marcoulides (2006)
Is the potential factor a trait explaining its indicators or is the potential factor explained by combination of indicators?	If trait: reflective If combination: formative	Kline (2016)
Do the indicators of the potential factor represent affects or causes of its potential factor?	If affects: reflective If causes: formative	Bollen and Bauldry (2011); Hair et al. (2017)
Are the indicators of the potential factor mutually interchangeable?	If yes: reflective If no: formative	Kline (2016)

To measure potential factors, the potential factors were arranged in two hierarchical layers of measurement models. The first layer consisted of a single layer of several potential factors that were measured with reflective measurement models. The second hierarchical layer was a higher-order layer, which consisted of a single higher-order potential factor and several lower-order potential factors (Hair et al., 2017). The higher-order potential factor captured the more abstract nature of the factor, while the lower-order potential factor captured the sub-dimensions of the higher-order factor. The relationship between the higher-order potential factors and the lower-order potential factor was formative in nature, whereas the relationship between indicators that specified the lower-order potential factors was reflective. In measurement models, arrows are used to distinguish between reflective and formative measurement indicators. One-way arrows are used to indicate the direction of the causal relationships between the potential factors and their indicators (Raykov & Marcoulides, 2006). The arrowhead signals which variable, potential factor, or indicator is explained in the measurement model. In the reflective measurement model, an arrowhead points toward the indicator; therefore, the indicator is explained by the potential factor. In the formative measurement model, an arrowhead points to the potential factor; thus, the potential factor is explained by the indicator. Figure 3.5 depicts the relationships between potential factors and their indicators in the different measurement models.

Figure 3.5 *Examples of measurement models. A. Reflective measurement model. B. Formative measurement model. C. Higher-order component measurement model*



A. B. C.

3.7.1.2 Development of reflective and formative measurement indicators

For the development of reflective and formative measurement indicators, several similar studies were consulted, and appropriate, previously validated questions were identified for use in this study. The reflective and formative indicators were then developed from these questions by modifying them to fit the specificities of the study and the chosen ordinal rating scale (Bhattacherjee, 2001; H. Chen, 2010; Thong et al., 2006). For example, if the original questions specified an information system, the questions were adapted to specify the SAM OLE. A seven-point Likert scale was used for the measurement of each indicator, which consisted of the two anchor points, "*Strongly Disagree*" (1) and "*Strongly Agree*" (7) (Finstad, 2010). Specific guidelines were devised to guide the composition of the reflective and formative measurement indicators. Thus, each set of measurement indicators for a particular potential factor should:

- Have a minimum of three measurement indicators (Hair et al., 2006; Raykov & Marcoulides, 2006);
- Be written in simple and unambiguous language;
- Be written as a question in accordance with the chosen rating scale; and
- Be guided by the causality direction of the indicator potential factor relationship.

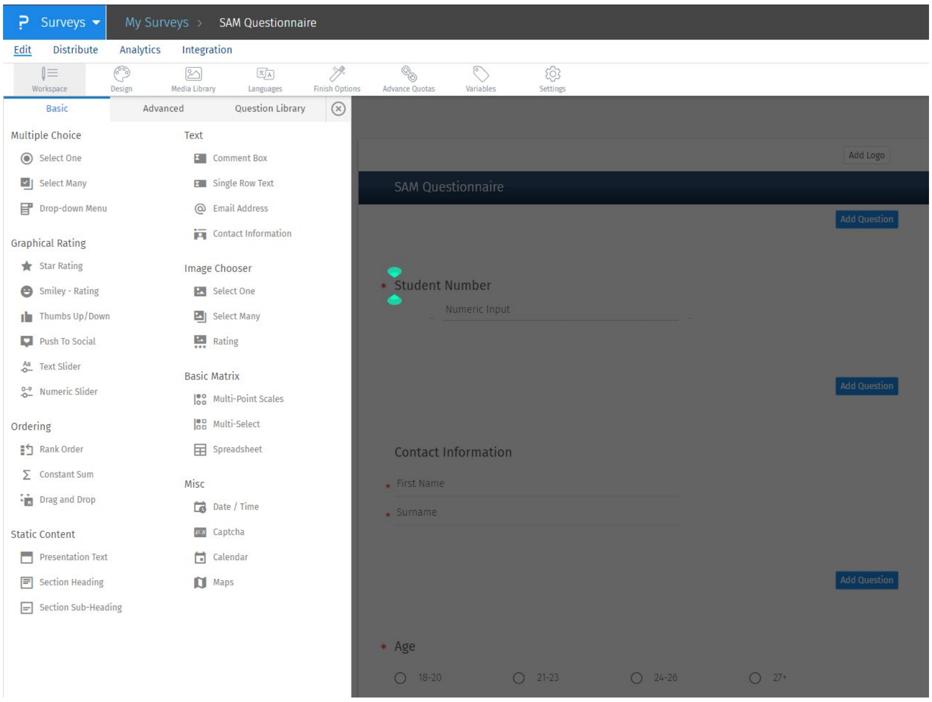
Once a draft version of the MIQ had been completed, a focus group was assembled to discuss the appropriateness of the draft. The focus group consisted of four members, of whom three were the supervisors of the study and one an academic member of the faculty, with previous experience in similar studies. Two of the supervisors as well as the researcher attended a workshop on structural equation modelling with an expert in the field prior to the development of the MIQ. The focus group was instructed to check that all items were composed according to the specific guidelines, and to provide critical feedback. The feedback provided by the focus group was then considered and used to improve the MIQ before it was digitised.

3.7.1.3 Digitisation of the MIQ and access

For ease of administration of the MIQ to a large group of participating students, a digitised version of the MIQ was made available. The MIQ was digitised using a licenced version of QuestionPro, obtained through the Department of e-Learning and Educational Technology at the CUT, Free State. The MIQ was digitised in the following manner:

1. Before the MIQ was digitised, a QuestionPro account was opened.
2. A new blank questionnaire was opened by accessing the Basic Question tab (Figure 3.6).
3. The blank questionnaire was then named SAM_Questionnaire.
4. Each question from the MIQ was then entered individually by first selecting an appropriate format in the Basic Question tab: Multiple Choice, Text, or Graphical Rating.
5. Once the MIQ had been digitised, the due date for completion was set to allow for five days of access.
6. Lastly, a unique hyperlink was generated and copied to the university's learning management system, Blackboard, to give students access to the MIQ (https://samquestionnaire.questionpro.com).

Figure 3.6 *QuestionPro basic question format options*



3.7.2 Collection and screening of data

3.7.2.1 Administration of MIQ

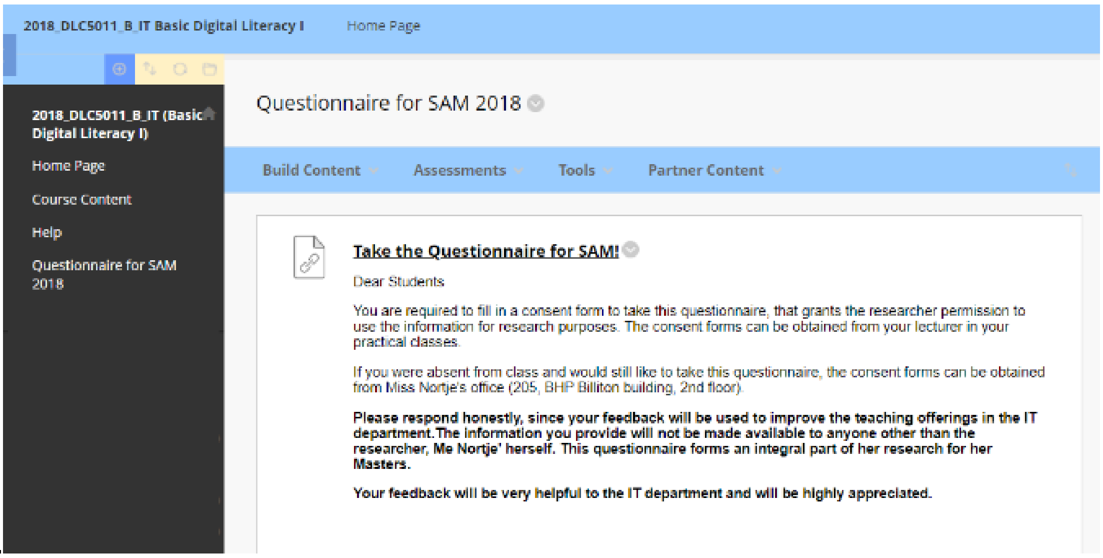
Prior to administering the MIQ to the participating students, a small-scale pilot study was performed in 2018 to assess the internal consistency reliability of the questions used in the instrument. The items of the MIQ were piloted with a convenience sample of undergraduate students registered in the Department of Information Technology. All these students had previously completed the Basic Digital Literacy module using the SAM OLE (n = 170). The Cronbach α was calculated for the students' response data to determine the internal consistency of each set of measurement indicators addressing a specific potential factor. The internal consistency reliability measure Cronbach α values for the pilot test ranged from 0.64 to 0.77, which were in an acceptable range.

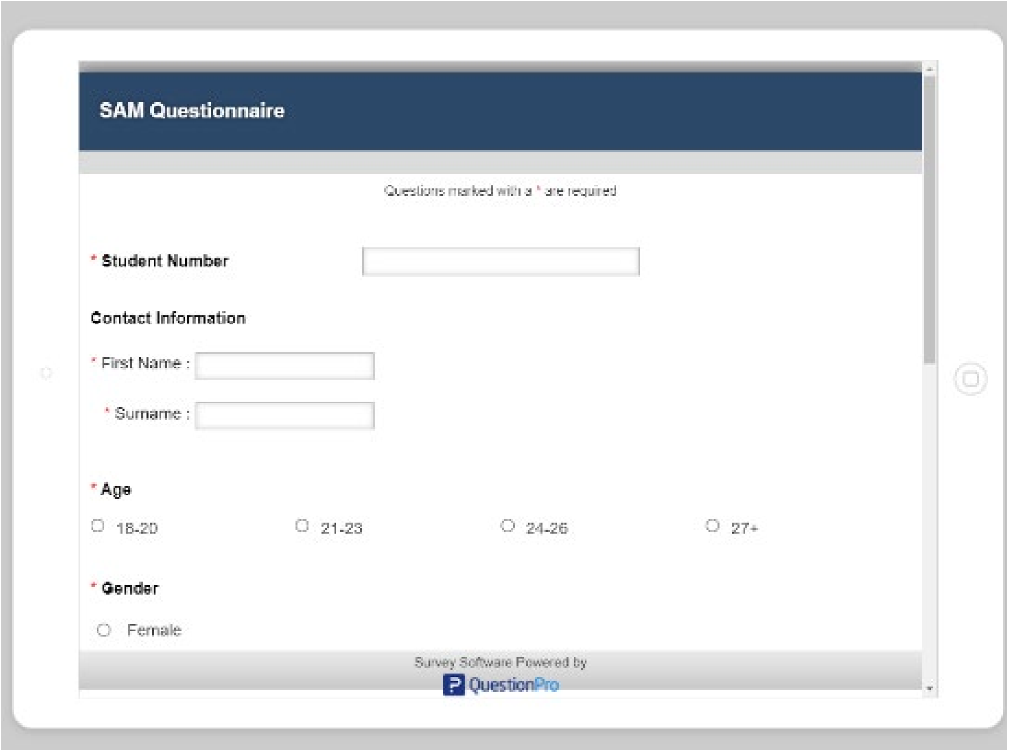
For this study, the MIQ was administered to a group of first-year students enrolled for the module Basic Digital Literacy. These students completed the module over 12 weeks, during which they engaged with the SAM OLE. After the completion of the module, the students were verbally informed of the study and the reason why the study was being conducted. The MIQ was administered to the students by staff members of the IT Department other than the reachers to mitigate the possible presence of a power relationship between the researcher and the students to prevent response bias. The students were requested to participate voluntarily, as the results of the study would provide knowledge about factors influencing first-year students' intention to continuously use the SAM OLE at the CUT. All student volunteers were then asked to complete a consent form (a copy of this consent form appears in Appendix B). After they had completed the consent form, the students were asked to complete the digitised MIQ in the computer laboratories of the Information Technology Department during the subsequent five days by executing the following steps:

1. Firstly, a student logged in to Blackboard with their personal university login credentials.
2. Thereafter, a student selected the module Basic Digital Literacy from the course list, then navigated to the content area referred to as "Questionnaire for SAM" and clicked on the QuestionPro link.
3. After clicking on the QuestionPro link, the student was redirected to the QuestionPro website.
4. On the QuestionPro website, the student accessed the digitised MIQ by clicking on the link.
5. Finally, the student then completed the digitised MIQ by following the instructions (Figure 3.7).

Figure 3.7 *Blackboard and QuestionPro student access pages. A. Blackboard access page depicting instructions to access the MIQ on the QuestionPro website. B. QuestionPro access page to the MIQ*

A.





B.

3.7.2.2 Capturing and screening of data

After students had completed the MIQ, the data were captured and screened. Once the five-day access period specified on the QuestionPro platform had passed, the MIQ closed automatically and thus prohibited any further entries. The data captured by the MIQ were stored on the QuestionPro platform using a secure unique username and password. The MIQ data stored on the QuestionPro platform were accessed, captured, and screened in the following manner:

1. The QuestionPro account was accessed using the unique username and password.
2. After accessing the account, the data were downloaded and saved by selecting the download button and Excel spreadsheet option from the Analytics tab, and then stored on an external hard drive ensuring password-protected access.
3. After saving the QuestionPro Excel file, the file consisting of 1003 student records (rows) and 26 columns containing student biographical and supplemental information, as well as the data related to the measurement indicators, was viewed to ensure that the data had been downloaded correctly.
4. After viewing the data, blank and incomplete rows were deleted.
5. Thereafter, all "straight liners" (records containing the same value for each question) were removed (Reuning & Plutzer, 2020).

6. The data were then scrutinised in terms of the supplementary information, and the records of students with prior knowledge of basic digital literacy were removed, as were records of repeating students.
7. Students were asked to specify how often they engaged with the SAM OLE; 14 students indicated that they did not engage with the platform at all; therefore, their responses were removed from the data set.
8. The student data were then anonymised by deleting the columns containing the student names and student numbers.
9. After removing blank, incomplete and "straight liner" rows, as well as records of students with prior knowledge of basic digital literacy, the final data file was saved and password-protected (Figure 3.8).

Figure 3.8 *Representation of the final data file after data screening*

Items for the data related to the measurement indicators

Items for the biographical and supplemental information

Record_ID	IR1	IR2	IR3	IF1	IF2	IF3	Age	Gender	Home Language	Do you own a computer?
1	5	6	3	6	1	7	1	1	1	1
2	6	4	2	6	1	4	1	1	2	2
3	6	1	7	2	1	3	3	2	2	1
4	2	5	7	6	5	3	4	2	9	2
5	6	0	7	1	0	3	2	2	4	2
6	4	2	4	6	6	3	1	3	13	1

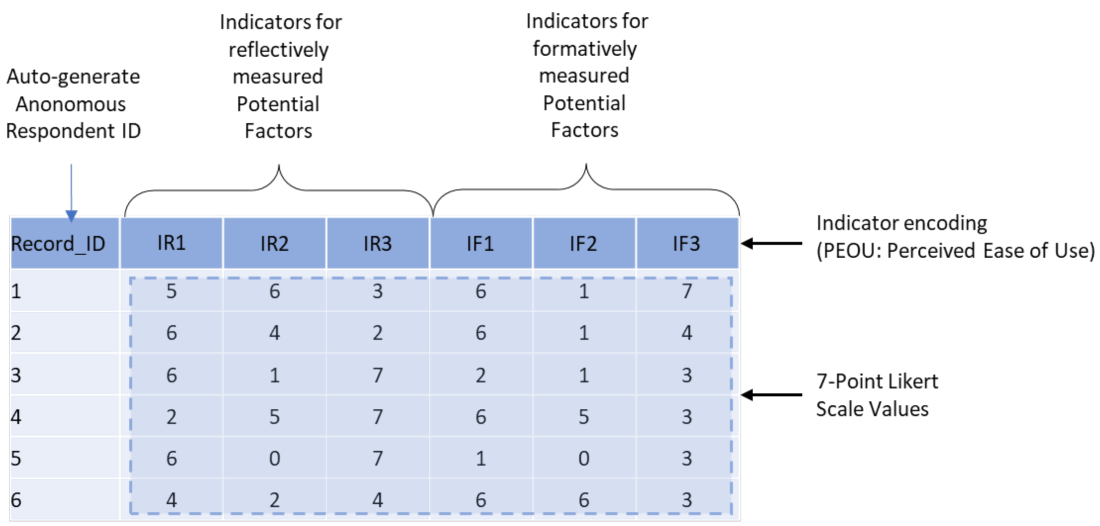
3.7.2.3 Pre-processing of data

After the preparation of the final Excel data file, it was processed for the data analysis phase of the project (Phases 2 and 3). The biographical and supplemental data were saved separately from the measurement indicator data in two new, separate data files. The file containing the biographical and supplemental data was used to calculate summary statistics using SPSS, while the file containing the measurement indicator data was analysed in SmartPLS. The data contained in the final Excel data file were processed in the following manner:

1. In order to maintain the integrity of the final Excel data file, it was duplicated and renamed.

2. The measurement indicator data in the duplicate file were deleted, while the biographical and supplemental data columns were retained.
3. The file containing biographical and supplemental data was then password-protected and saved (Figure 3.9A).
4. Thereafter, the final Excel data file was duplicated for a second time and renamed.
5. The biographical and supplemental data columns in this file were then deleted, while the measurement indicator data columns were retained.
6. The file containing the measurement indicator data was then also password-protected and saved (Figure 3.9B).
7. Lastly, in Excel, the file containing the biographical and supplemental data and the file containing the measurement indicator data were converted to comma-separated (CSV) files and stored on an external hard drive before it was used for data analysis.

Figure 3.9 *Representation of the data files. A. Data file containing measurement indicator data. B. Data file containing biographical and supplemental data*



Record_ID	IR1	IR2	IR3	IF1	IF2	IF3
1	5	6	3	6	1	7
2	6	4	2	6	1	4
3	6	1	7	2	1	3
4	2	5	7	6	5	3
5	6	0	7	1	0	3
6	4	2	4	6	6	3

A.

Auto-generate Anonomous Respondent ID

Name this category

Indicator encoding (PEOU: Perceived Ease of Use)

Values corresponding with the menu items of the MIQ

Record_ID	Age	Gender	Home Language	Do you own a computer?
1	1	1	1	1
2	1	1	2	2
3	3	2	2	1
4	4	2	9	2
5	2	2	4	2
6	1	3	13	1

B.

3.7.3 Analysis of data

3.7.3.1 Summary statistics of the student population

Summary statistics of the student biographical and supplementary data items were calculated to establish the occurrence frequency of the different items. These frequencies were calculated using the SPSS application. Frequency tables for the different items were generated using SPSS, in the following manner:

1. The SPSS application was launched, and a project file with a unique file name was created, which was then saved on an external hard drive.
2. The CSV file containing the biographical and supplemental information was then imported into SPSS by accessing the *File* tab, selecting the *Open* menu item, and then choosing the file from the hard drive.
3. The data in the project file was encoded by selecting the Design view and specifying the values with specific codes (Table 3.5).
4. The frequencies of the encoded values of the different biographical data items were determined by selecting the frequency procedure from the *Descriptive Statistics* tab.
5. Lastly, the frequency tables were displayed in the SPSS Output window, which was then saved as an output file.

Table 3.5 *Item codes used for calculating summary statistics in SPSS*

Data item	SPSS code	Value
Biographical items		
Age	1	> 18 ≤ 20
	2	> 20 ≤ 23
	3	> 24 ≥ 26
	4	> 27
Gender	1	Female
	2	Male
	3	Other
Home language	1	Afrikaans
	2	English
	3	Ndebele
	4	Northern Sotho
	5	Sotho
	6	Swati
	7	Tsonga
	8	Tswana
	9	Venda
	10	Xhosa
	11	Zulu
	12	Other
Prior knowledge of digital literacy	1	Computer-aided technology (CAT)
	2	Information technology (IT)
	3	Neither of the above

Data item	SPSS code	Value
Qualification (National Diploma, Bachelor's degree, or Higher certificate)	1	Accountancy and Internal Auditing
	2	Agriculture Management
	3	Biomedical Technology
	4	Built Environment
	5	Clinical Technology
	6	Community Development Work
	7	Design and Studio Art
	8	Education
	9	Environmental Health
	10	Financial Information Systems
	11	Human Resources Management
	12	Marketing
	13	Public Management
	14	Radiography
	15	Somatology
	16	Tourism Management
	17	Engineering
	18	Other
Supplemental items		
Computer access	1	Has access to a computer
	2	Does not have access to a computer
Smartphone access	1	Has access to a smartphone
	2	Does not have access to a smartphone
	1	One semester

Data item	SPSS code	Value
Number of semesters engaged with SAM	2	Two semesters
	3	Three semesters
	4	Four semesters
	5	More than four semesters
Regularity of SAM usage	1	Not at all
	2	Less than once a week, about once a week
	3	Two or three times a week
	4	More than three times a week
Time spent using SAM	1	Less than 30 minutes
	2	Between 31 and 60 minutes
	3	Between 61 and 90 minutes
	4	More than 90 minutes

3.7.3.2 Assessment of the reflective measurement model

Prior to measuring the structural model, the measurement models were, first, assessed for validity and reliability. The respective reflective measurement models were assessed in terms of several validation measures, which included convergent validity, discriminant validity and internal consistency reliability. The convergent validity of the reflective measurement indicators indicates the extent to which a reflective measurement indicator correlates positively with the other indicators in the same set belonging to a particular potential factor (Hair et al., 2017). Convergent validity was measured by means of indicator outer loadings and the average variance extracted (AVE) criteria (Hair et al., 2017). An indicator outer loading is the single regression result for a measurement indicator in a measurement model. These outer loadings show how much each indicator contributes to its potential factor. The AVE is the mean of the squared outer loadings of a set of indicators belonging to a particular potential factor. Discriminant validity measures how distinct a set of indicators of a particular reflective measurement model is when compared to the other measurement models (Gefen et al., 2011; Hair et al., 2017). Discriminant validity was measured by means of cross loadings, the Fornell-Larcker and heterotrait-monotrait (HTMT) criterion. To determine how distinct different measurement models are when compared, the cross loadings are calculated as cross-correlations between the outer loadings of the different sets of indicators belonging to a particular potential factor. The Fornell-Larcker criterion is also a measure of distinctness between the sets of indicators belonging to a potential factor (Fornell & Larcker, 1981). The Fornell-Larcker criterion posits that discriminant validity is established when a potential factor accounts for more variance in its associated measurement indicators than it shares with another potential factor in the same structural model.

A more recent calculation of discriminant validity is the HTMT (Henseler et al., 2014). The HTMT is the average of the correlations of indicators across potential factors (heterotrait correlations) relative to the average of the correlations of indicators within the same potential factor (monotrait correlations). Internal consistency reliability is a type of reliability used to determine the validity of a set of indicators belonging to a particular potential factor (Hair et al., 2017). Internal consistency reliability is measured by means of the Cronbach α and the composite reliability. The Cronbach α is a conservative estimate of the reliability amongst the indicators in a set based on the average inter-correlations amongst the indicators and the assumption that all outer loadings are equal. In turn, the composite reliability is a less conservative estimate of reliability, because the equality assumption is not assumed. The various reflective validation measures, criteria, threshold values and formulae are listed in Table 3.6.

Table 3.6 *Validation measures, criteria, threshold values and formulas of the reflective measurement model*

Validation measure	**Criterion**	**Threshold**	**Procedure and formula**
Convergent validity	Outer loadings	> 0.7	Outer loadings are single regression results calculated by SmartPLS with a particular indicator in the reflective measurement model as a dependent variable and the potential factor as an independent variable.
	AVE	> 0.5	$$\text{AVE} = \left(\frac{\sum_{i=1}^{K} l_i^2}{K}\right) \quad (1)$$ Where K represents the number of indicators belonging to a potential factor; and Where l_i represents outer loadings.

Validation measure	Criterion	Threshold	Procedure and formula
Discriminant validity	Cross loadings	Indicator’s outer loadings (single regression) with a potential factor should be greater than cross-loadings with other potential factors.	$$\begin{array}{cccc} & Y_1 & Y_2 & Y_3 \\ X_1 & \boldsymbol{W_{11}} & - & - \\ X_2 & \boldsymbol{W_{12}} & - & - \\ X_3 & - & \boldsymbol{W_{21}} & - \\ X_4 & - & \boldsymbol{W_{22}} & - \\ X_5 & - & - & \boldsymbol{W_{31}} \\ X_6 & - & - & \boldsymbol{W_{32}} \end{array} \quad (2)$$ Where $Y1, Y2, Y3$ represents the potential factors; Where $X_1 - X_6$ represents indicators; and Where $W_{11}, W_{12}, W_{21}, W_{22}, W_{31}, W_{32}$ represent the indicator outer loadings.
	Fornell-Larcker	The square root of the AVE of each potential factor should be greater than its highest correlation with any other potential factor.	$$\begin{array}{ccccc} & Y_1 & Y_2 & Y_3 & Y_4 \\ Y_1 & \sqrt{AVE_{y1}} & & & \\ Y_2 & Corr_{Y_1Y_2} & \sqrt{AVE_{y2}} & & \\ Y_3 & Corr_{Y_1Y_3} & Corr_{Y_2Y_3} & \sqrt{AVE_{y3}} & \\ Y_4 & Corr_{Y_1Y_4} & Corr_{Y_2Y_2} & Corr_{Y_3Y_3} & \sqrt{AVE_{y4}} \end{array} \quad (3)$$ Where $Y1, - Y4$ represents the potential factors; and Where $Corr_{y1-y4}$ represents a correlation between potential factors.
	HTMT	> ≠1	$$\mathrm{HTMT}_{ij} = \underbrace{\frac{1}{K_iK_j}\sum_{g=1}^{K_1}\sum_{h=1}^{K_1} r_{igjh}}_{\text{Average HTHM}} \div \left(\underbrace{\frac{2}{K_i(K_i-1)}\cdot\sum_{g=1}^{K_i-1}\sum_{h=g+1}^{K_i} r_{ig,ih}\cdot\frac{2}{K_j(K_j-1)}\cdot\sum_{g=1}^{K_j-1}\sum_{h=g+1}^{K_j} r_{jg,jh}}_{\text{Geometric mean of the average HTHM correlation of potential factor } K_1 \text{ and the average HTHM correlation of potential factor } K_2}\right)^{\frac{1}{2}} \quad (4)$$ Where K_i represents the number of indicators belonging to an independent potential factor; and Where K_j represents the number of indicators belonging to a dependent potential factor.

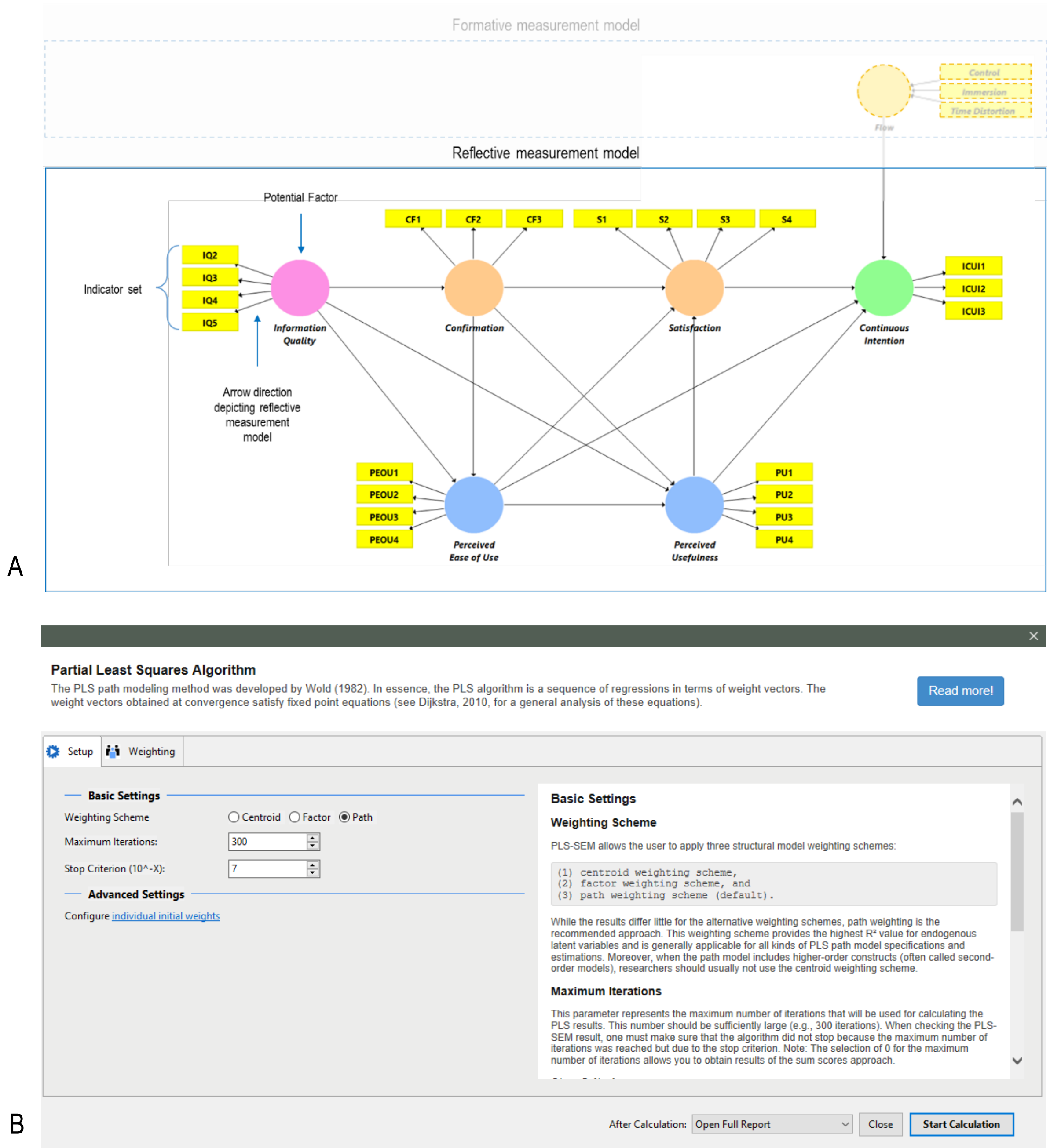
Validation measure	Criterion	Threshold	Procedure and formula
Internal consistency reliability	Cronbach α	α > 0.7	$$\alpha = \left(\frac{K}{K-1}\right) \cdot \left(1 - \frac{\sum_{i=1}^{K} l_i^2}{l_p^2}\right) \quad (5)$$ Where K represents the number of indicators belonging to a potential factor; and l_i represents the variance of the indicator variable i of a specific potential factor, measured with K indicators (i = 1, …, M), and is the variance of the sum of all M indicators of that potential factor.
	Composite reliability	> 0.7	$$\rho_c = \frac{(\sum_{i=1}^{K} l_i)^2}{(\sum_{i=1}^{K} l_i)^2 + \sum_{i=1}^{K} var(e_i)} \quad (6)$$ Where li symbolises the standardised outer loading of the indicator variable i of a specific potential factor measured with K indicators, Where e_i is the measurement error of indicator variable i, and $var(ei)$ denotes the variance of the measurement error.

Several steps were followed in SmartPLS to determine the validity and reliability of the reflective measurement models. The validity and reliability were assessed using SmartPLS in the following manner:

1. The SmartPLS application was launched, and then a project file was created with a unique file name.
2. The file was then saved on an external hard drive.
3. The CSV file containing the measurement indicator data was then imported into the SmartPLS project by accessing the *File* tab, selecting the *Import Data File* menu item, and then choosing the file from the hard drive.
4. Once the measurement indicator data had been imported, each set of measurement indicators belonging to a potential factor was selected, one by one, from the indicator list and dragged onto the graphical workspace referred to as the Modelling window, where the indicators were represented as rectangles containing an indicator code.

5. After dragging an indicator set onto the Modelling window, the indicators were linked by arrows to an autogenerated, unnamed circle representing a potential factor, which was then named appropriately.
6. The potential factors were then connected with arrows using a click and drag mouse action while ensuring the correct direction of the arrows (Figure *3.10*A).
7. Thereafter the *partial least squares (PLS) algorithm* was executed by selecting the algorithm in the main menu, retaining the default settings in the popup window, and clicking on the Start Calculation button (Figure *3.10*B).
8. After executing the *PLS algorithm*, several tables containing the validation measures could be accessed from the Results table at the bottom of the graphic user interface.

Figure 3.10 *Reflective measurement models and SmartPLS settings window. A. Example of connections consisting of indicator sets, and potential factors displayed in the modelling window. B. Popup window in SmartPLS depicting settings for the PLS algorithm*



3.7.3.3 *Assessment of the formative measurement model*

After the reflective measurement models had been assessed and found to be valid and reliable, the formative measurement models were tested. In contrast to the reflective measurement models, the formative measurement models were tested with a different set of validation measures, because of the differing directional causality relationship between indicators and the potential factor to which the indicators belong. These models are assessed in terms of two validation measures, which include the assessment of collinearity and outer weight significance and relevance. These two validation measures were used to test the formative indicator contribution to the potential factors, as well as the significance of their contribution. Collinearity indicates the extent of the correlation between a set of formative indicators belonging to a potential factor (Hair et al., 2017; 2021). Because of the directional causality relationship between a potential factor and its indicators, correlations between these indicators should be low. Two measures of collinearity can be used, the variance inflation factor (VIF) and tolerance. However, in recent times, the VIF (specifically the outer VIF values) statistic is usually reported, because these two measures are reciprocal and convey the same information (Hair et al., 2017; 2021). VIF is a measure of the amount of multicollinearity that exists amongst a set of formative indicators. The assessment of the outer weight and its significance is a validation measure for assessing the contribution of a formative indicator to its associated potential factor. Thus, the outer weight significance and relevance measure the variance contribution of a formative indicator to its associated potential factor (Hair et al., 2017; 2021). Before running the *PLS algorithm*, as listed for the reflective validation measures, a few additional steps were required to specify the higher-order measurement model in SmartPLS:

1. After dragging the reflective indicator sets onto the Modelling window, all the indicators sets of the lower-order potential factors were then dragged as a single group onto the Modelling window.
2. The indicators were linked by arrows to an autogenerated, unnamed circle representing the higher-order potential factor, which was then appropriately named.
3. Thereafter, the lower-order potential factor indicator sets (in this study, three sets) were dragged onto the Modelling window one by one.
4. The indicators of each set were linked by arrows to an autogenerated, unnamed circle representing the lower-order potential factor, which was then appropriately named.
5. The lower-order potential factors were then linked to the higher-order potential factor with arrows.
6. Thereafter, latent variable scores were generated by running the PLS algorithm retaining all the default settings in the popup window.
7. The latent variable scores were accessed from the Results table at the bottom of the graphic user interface, copied, and pasted to the CSV file containing the data.
8. Before finally executing the *PLS algorithm*, the indicators linked to the higher-order potential factor (step 2) were deleted.

9. Lastly, the *PLS algorithm* was then executed to generate the validation measures, which were accessed from the Results table at the bottom of the graphic user interface.

The various formative measurement model validation measures, criteria, threshold values and formulae are listed in Table 3.7.

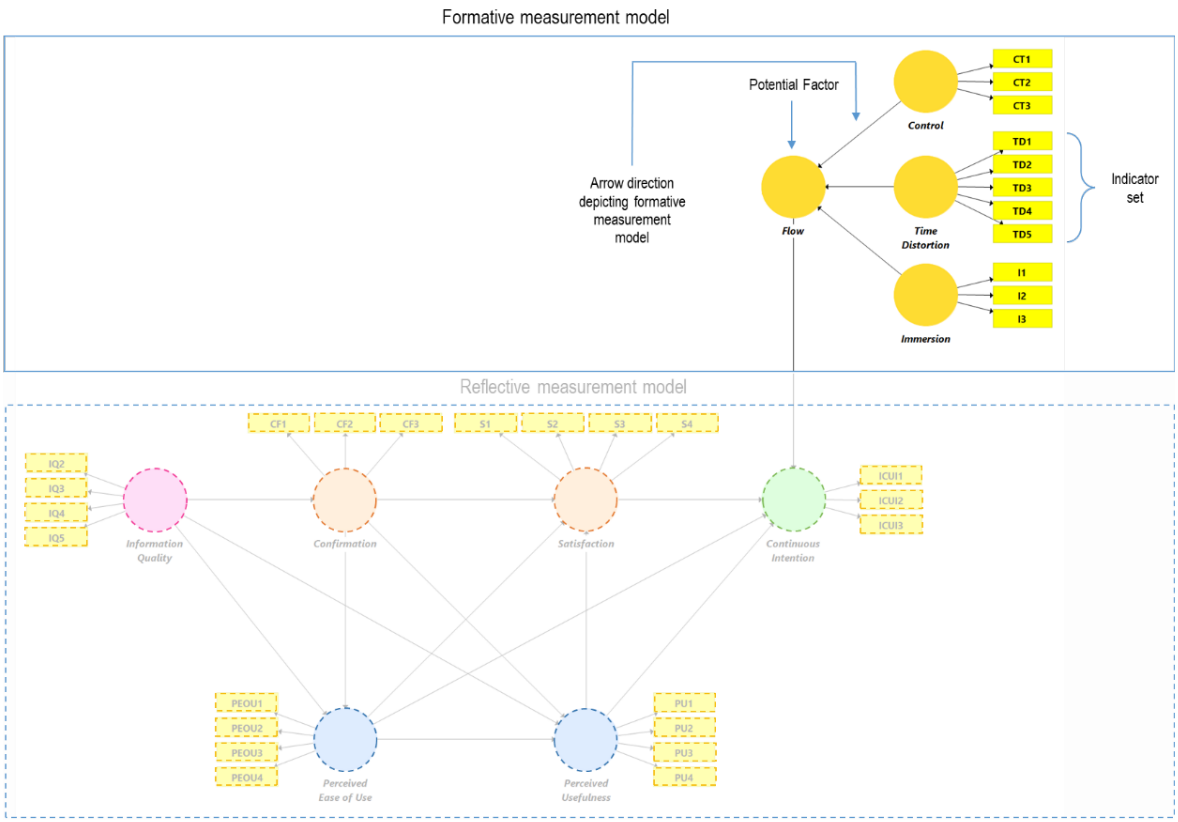
Table 3.7 *Formulas and threshold values used to guide the assessment of the formative measurement model*

Validation measure	Criterion	Threshold	Procedure and formula
Collinearity	Outer VIF	VIF < 3	$$VIF_i = \frac{1}{1-R_i^2} = \frac{1}{Tolerance} \quad (7)$$ Where R_i^2 represents the unadjusted coefficient of determination for regressing the i^{th} formative indicators on the remaining formative indicators.
Outer weight significance and relevance	p Value	p Value of outer weight ≤ .001	Outer weights are partial multiple regression results calculated by SmartPLS with a particular indicator in the formative measurement model as an independent variable and the potential factor as a dependent variable.

3.7.3.4 Hierarchical arrangement of the measurement models

In this study, several reflective models and a higher-order measurement model were used to measure the potential factors. The reflective measurement models were in the first layer of the hierarchy of measurement models and measured the potential factors, *Information Quality*, *Confirmation*, *Satisfaction*, *Perceived Ease of Use*, *Perceived Usefulness*, and *Continuous Use Intention*. In contrast, the formative measurement model was part of a higher-order measurement model in the second layer of the hierarchy of measurement models, where *Flow* was the higher-order potential factor connected to three lower-order potential factors, *Control*, *Time Distortion,* and *Immersion*. Figure 3.11 depicts the reflective measurement models and the higher-order measurement model used in this study.

Figure 3.11 *Measurement models used to measure the potential factors identified for this study as displayed in the modelling window*



3.8 Methods for Phase 3: Assessment of the structural model

3.8.1 Assessment of structural model

After the assessment of the measurement models and before the assessment of the structural model, the structural model was, first, assessed in terms of collinearity between the potential factors. In order to determine the relationships between the independent and dependent potential factors, coefficients are derived from regression estimates. However, these point estimates and standard errors may be biased because of strong correlations between factor pairs. Therefore, there exists the potential for strong correlations between potential factors, which necessitates an assessment of collinearity (Hair et al., 2021). Collinearity was, thus, assessed in terms of the validation measure of Inner VIF, similar to the Outer VIF assessed for the formative measurement model (Table 3.8). The Inner VIF values were accessed from the Results table at the bottom of the Modelling window after executing the *PLS algorithm*. Thereafter, the Inner VIF values were inspected to ascertain if they conformed to the threshold value.

Table 3.8 *Validation measure, criterion, threshold value and formula for collinearity*

Validation measure	Criterion	Threshold	Formula
Collinearity	Inner VIF	VIF < 3	$$VIF_j = \frac{1}{1 - R_j^2} \quad (8)$$ Where R_j^2 represents the R^2 value obtained for regressing the j^{th} independent potential factor on the remaining independent potential factors.

3.8.2 Analysis of path coefficients

Once it was established that collinearity did not exist between potential factors, the relational hypotheses that describe the relationships between factors were tested. This was accomplished by estimating path coefficients describing the path relationships between potential factors in the structural model (Table 3.9). The path coefficients correspond to standardised beta values (ß) in a regression analysis(Hair et al., 2021). The path coefficients represent the amount of variance in the dependent potential factors explained by all the independent potential factors linked to dependent potential factors. The significance of the path coefficients was determined through Bootstrapping and calculation of t values, while the relevance was described in terms of the strength of the relationships between the potential factors (Hair et al., 2021). The t values were used to determine the significance of the relational hypotheses of the structural model at an alpha (α) value of .05.

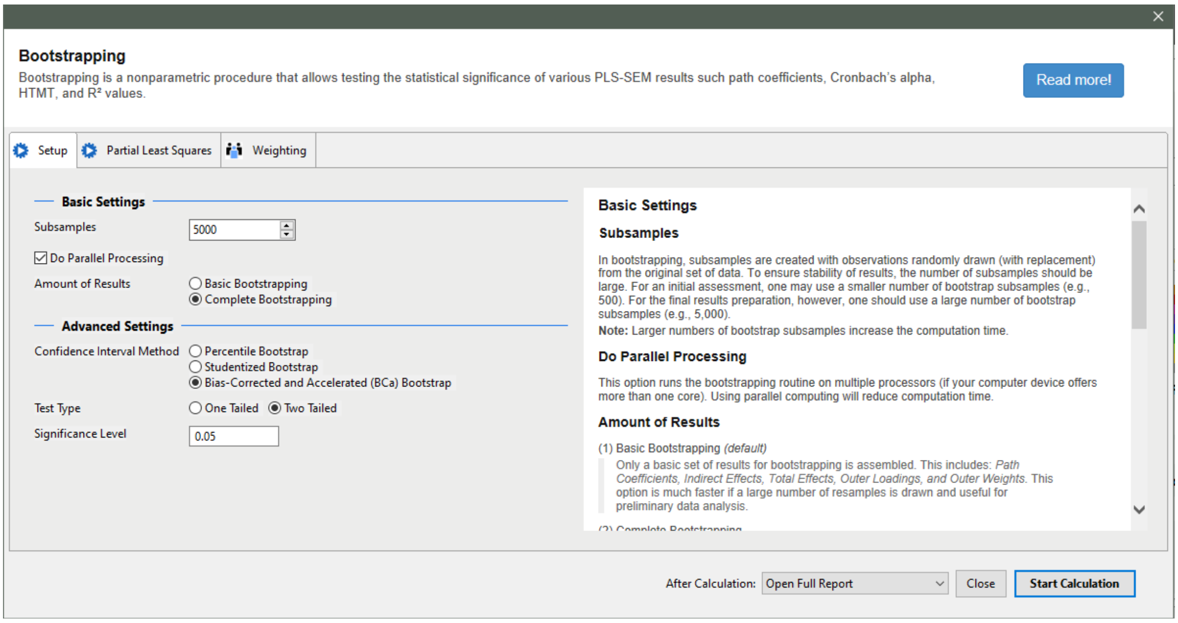
Table 3.9 *Validation measures, criteria, threshold values and procedure for the validation of the structural model*

Validation measure	Criterion	Threshold	Procedure
Path coefficient statistical significance and relevance	p Value	p Value of path coefficients ≤ .005	Bootstrap procedure executed (Subsamples: 5000)

The *Bootstrapping* procedure was executed in SmartPLS to determine the significance and relevance of the path coefficients of the structural model. The significance and relevance were determined by executing the following steps:

1. After executing the *PLS algorithm*, the *Bootstrapping* procedure was selected from the Calculate menu (Figure 3.12).
2. The number of sub-samples was then set to 5000 and the test type to 2-tailed in the popup window.
3. Thereafter, the Start Calculation button was clicked to access the full report at the bottom of the Modelling window.

Figure 3.12 *Popup window in SmartPLS depicting settings for the Bootstrapping procedure*



3.8.3 Explanatory power, effect size and predictive accuracy of the structural model

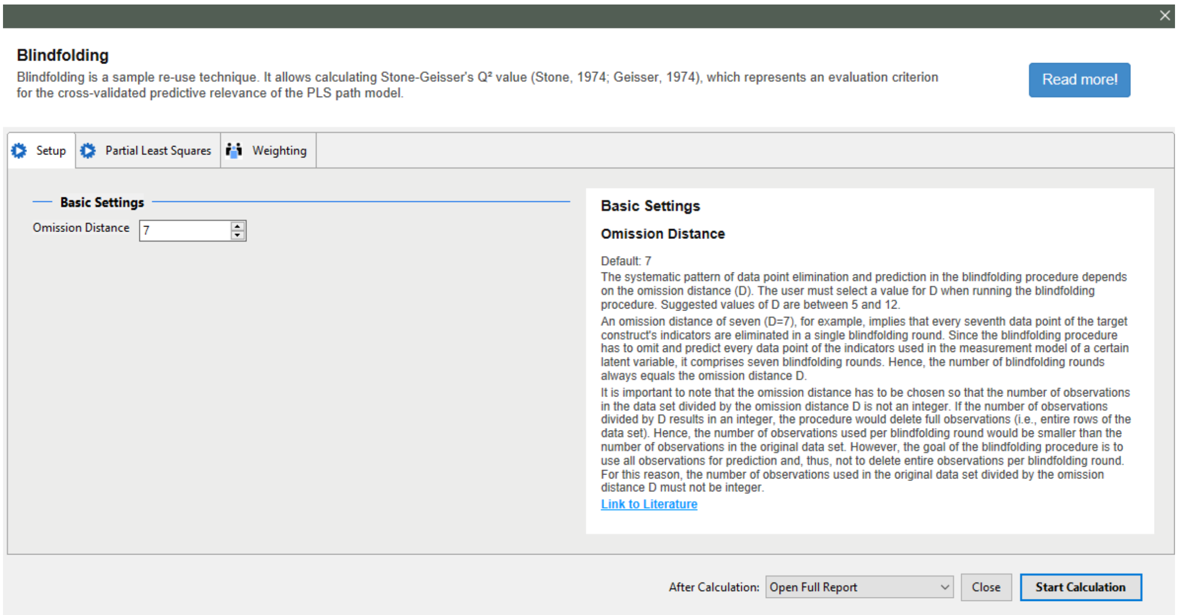
The explanatory power, effect size and predictive accuracy of the structural model were determined. The explanatory power, as the coefficient of determination (R^2), was calculated to express the strength of the hypothesised relationships between the potential factors in the structural model. In order to determine the structural model's explanatory power, the coefficient of determination for each of the dependent potential factors was calculated, and the significance was determined through Bootstrapping and the calculation of t-values (Hair et al., 2017; Keith, 2019). The coefficient of determination expresses the proportion or fraction of a dependent potential factor's total variance explained by its independent potential factor(Hair et al., 2021). Once the model's explanatory power had been determined, the effect size (f^2) of an independent potential factor on a dependent potential factor within the structural model was calculated (Hair et al., 2021). Lastly, the model's out-of-sample predictive power or predictive relevance was determined by calculating the Stone-Geisser's value through the sample reuse technique of Blindfolding (Geisser, 1974; Stone, 1974). As such, the Q^2 combines aspects of out-of-sample prediction and in-sample explanatory power (Shmueli et al., 2016; Hair et al., 2017). Table 3.10 depicts the measures, criteria, threshold values and formulas for the coefficient of determination, effect size and predictive accuracy.

Table 3.10 *Validation measures, criteria, threshold values, procedure and formulas of coefficient of determination, effect size and predictive accuracy*

Validation measure	Criterion	Threshold	Formula	
Coefficient of determination	R^2	Magnitude: < 0.19 Negligible ≥ 0.19 ≤ 0.33 Weak > 0.33 ≤ 0.67 Moderate > 0.67 Substantial (Chin, 1998)	$R^2 = \frac{SS_{\text{regression}}}{SS_{\text{total}}}$ Where $SS_{\text{regression}}$ is a measure of the variance explained in the dependent variable by the independent variables.	(9)
Effect size	F^2	Effect: < 0.02 Negligible ≥ 0.02 ≤ 0.15 Small > 0.15 ≤ 0.35 Medium > 0.35 Large (Hair et al., 2017)	$F^2 = \frac{R^2{}_{included} - R^2{}_{excluded}}{R^2{}_{included}}$ Where $R^2{}_{included}$ and $R^2{}_{excluded}$ are the R^2 values of the dependent potential factors when a selected independent potential factor is included in or excluded from the structural model.	(10)
Predictive relevance	Q^2	Effect: < 0.02 Negligible ≥ 0.02 ≤ 0.15 Small > 0.15 ≤ 0.35 Medium > 0.35 Large (Hair et al., 2017)	Blindfolding procedure executed (Omission distance: 7)	(11)

1. After executing the Bootstrapping procedure, the Blindfolding procedure was selected from the Calculate menu (Figure 3.13).
2. The default omission distance setting was retained (7).
3. Thereafter, the Start Calculation button was clicked to access the full report below the Modelling window.

Figure 3.13 *Pop-up window in SmartPLS depicting settings for the Blindfolding procedure*



3.9 Summary

This chapter defined the conceptualisation and the described the methods of the study. The conceptualisation entails the approach, conceptual framework, student population and materials of the study. In this study a positivistic viewpoint was observed during this study entailing a deductive reasoning where a sequential multi-method approach was followed to gather and analyse quantitative data. The data for this study was voluntarily collected from 793 of the first-year students from the four faculties at the CUT enrolled for the Basic Digital Literacy service module. The software applications used during the project to gather, prepare, and analyse data were QuestionPro and Blackboard, Microsoft Excel and SPSS and SmartPLS respectively. The methods section of the study described the methods used to obtain the results for each of the three phases of the study. These three phases include the methods to construct the structural model, the assessment of the measurement models and the assessment of the structural model. Phase 1 firstly entailed a description of how the literature search was conducted to identify relevant literature and theories as well as potential factors that could influence students' intention to continuously use the Basic Digital Literacy OLE. Then a description followed of how these factors were used to construct a structural model. Lastly it describes how the structural model, containing potential factors and the target factor, were then used to formulate the relational hypotheses that were tested in this study. Phase 2 entailed a description of how the potential factors and the target factor were operationalised by specifying observable variables in several measurement models, and how they were assessed for their reliability and validity. Phase 3 entailed a description of how the structural model was validated and assessed, and the relational hypotheses tested, as well as how the hypotheses were tested to establish which of the potential factors were actual factors that influenced students' intention to continuously use the Basic Digital Literacy OLE.

Chapter 4

Structural model for students' intention to continuously use the skills assessment manager online learning environment

4.1 Introduction

In the first phase of this study, a structural model was constructed in SmartPLS, which depicts the potential factors and the target factor and their relationships with one another. The contributions of the potential factors in their various relationships to a student's intention to continuously use the SAM OLE were ultimately measured, and the actual factors were identified from the potential factors. Therefore, the sub-question that was answered in Phase 1 was:

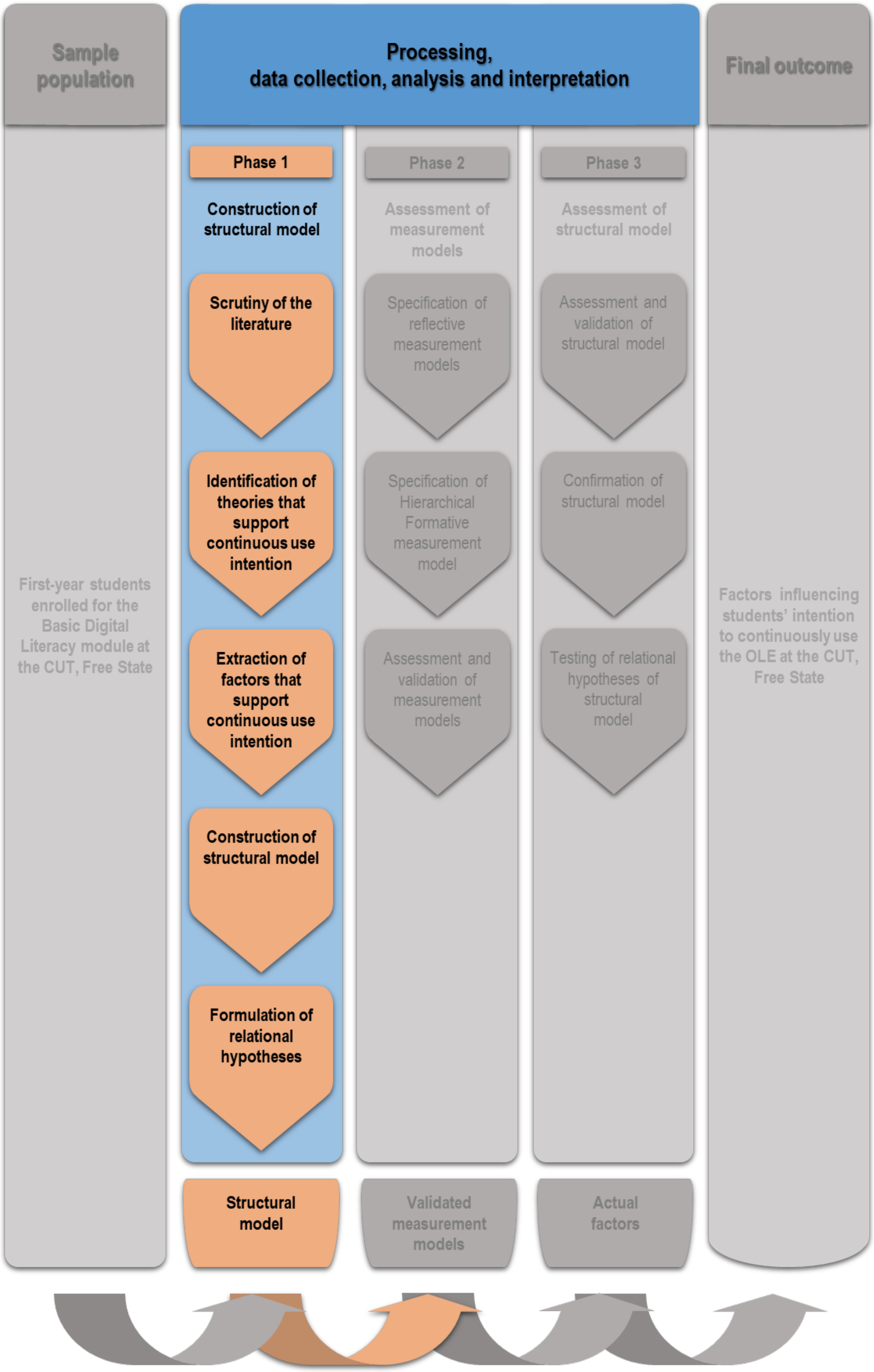
> *Which theories and potential factors can be used to construct a structural model containing potential factors that influence students' intention to continuously use the SAM OLE??*

In order to answer the research sub-question, the following actions were undertaken:

1. A literature review was conducted to identify relevant theories and potential factors that would aid in the identification of actual factors that could contribute to the prediction of students' intention to continuously use the SAM OLE.
2. The potential factors were then used to construct a structural model depicting the unidirectional relationships between the potential factors and the target factor.
3. Once the structural model had been constructed, the relational hypotheses relating to the relationships between the potential factors and the target factor were derived.

Figure 4.1 depicts how Phase 1 relates to the other components in the conceptual framework of this study.

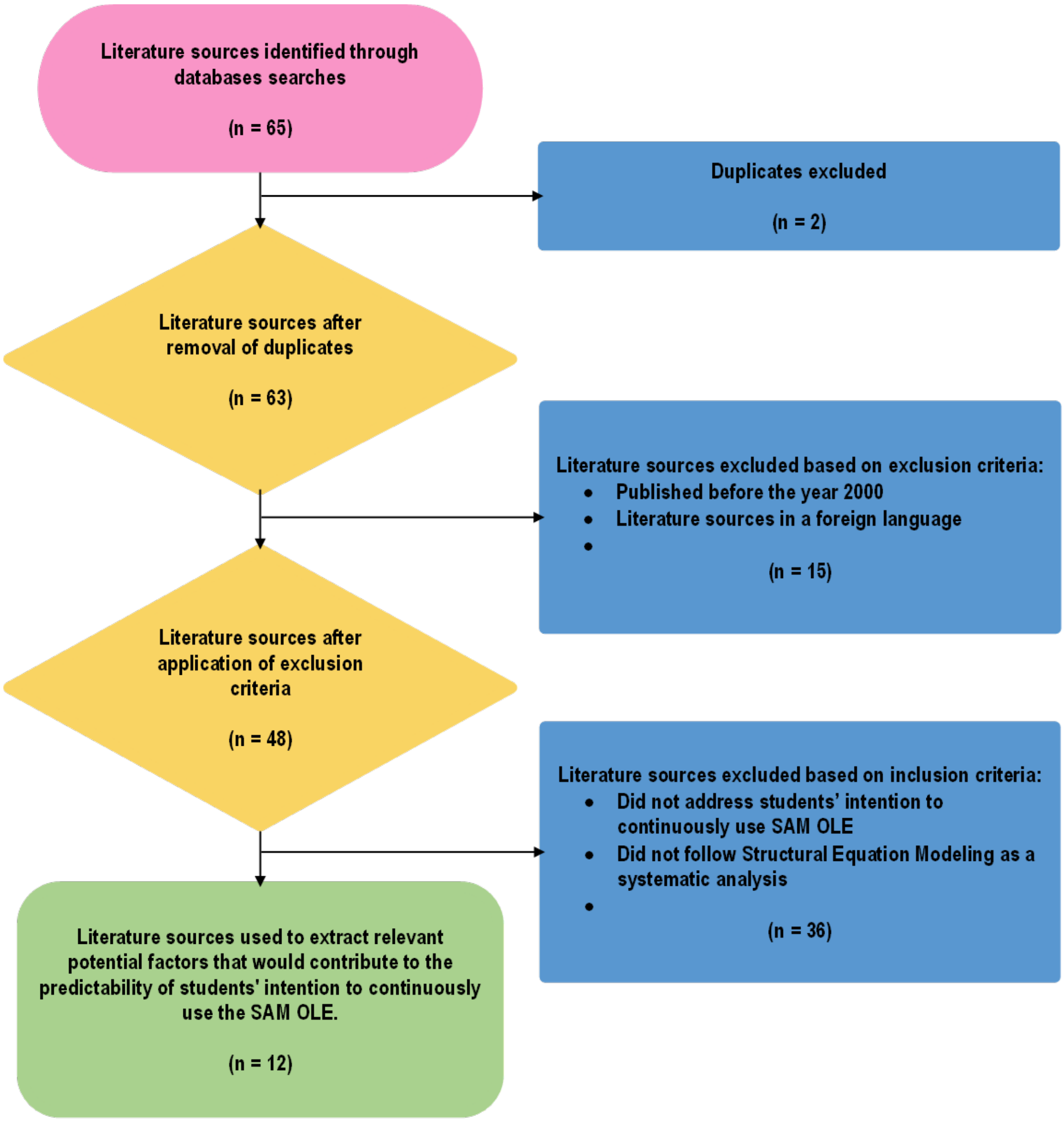
Figure 4.1 *Conceptual framework depicting objectives of the different phases, highlighting Phase 1*



4.2 Literature sources used to extract potential factors

After undertaking an extensive review of the literature, a collection of several suitable literature sources was identified and deemed suitable for scrutiny for relevant theories and potential factors that could predict students' intention to continuously use the SAM OLE. Initially, 65 literature sources were identified and then assessed for their eligibility for inclusion in this study (Figure 4.2). After the removal of the duplicate sources and the exclusion of sources published before the year 2000, the sources were then inspected further to determine their eligibility for extracting potential factors. This inspection revealed 12 sources that contained theories and factors related to students' intention to continuously use OLEs and follow SEM procedures.

Figure 4.2 *Identification of relevant literature sources suitable for the extraction of potential factors*



After identifying the 12 eligible literature sources, the sources were scrutinised further for relevant theories from which potential factors that influence students' intention to continuously use the SAM OLE could be extracted. These literature sources addressed students' intention to continuously use an OLE, mainly in the context of higher education. However, Suzianti and Paramadini (2021) address the interaction of teacher respondents with an OLE in a primary school setting (No. 1 in Table 4.1). Those sources that focused on higher education, address the intention to continuously use an OLE by undergraduate students registered for courses unrelated to Information Technology (Table 4.1). These courses include languages, management, and various courses in education. One of the sources related to higher education also addressed gamification (No. 2) in the assessment of students' intention to continuously use an OLE. These eligible literature sources covered 13 different theories, which addressed more than 50 factors that had the potential to be included in this study. The different theories originated from the information systems field and cognitive behavioural psychology. The theories from the information systems field were TAM, TTF, technology continuance (TCT), information systems success (ISS) and subjective task value (STV), while the theories from the cognitive behavioural psychology field were planned behaviour (TPB), information systems expectation-confirmation (ECM), expanded ECM, expectation-disconfirmation (EDT), decomposed expectation-disconfirmation (DED), cognitive model (COG), flow and the fairness theory.

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Table 4.1 *Descriptions of literature sources used to extract potential factors*

Literature source No.	**Reference**	**Brief description of content**	**Relevant factors**
1	Suzianti, A., & Paramadini, S. A. (2021). Continuance intention of e-learning: The condition and its connection with open innovation *Journal of Open Innovation: Technology, Market, and Complexity*, 7(1).	The ECM and modified ISS theories, with teacher self-efficacy as a latent factor, were used to construct a model that predicts teachers' intention to continuously use OLE.	*Information Quality, System Quality* affected *Perceived Usefulness* *System Quality, Teachers' Self-Efficacy* affected *Satisfaction* *Perceived Usefulness* affected *Satisfaction* and *Satisfaction* affected *Continuance Use Intention*
2	Vanduhe, V. Z., Nat, M., & Hasan, H. F. (2020). Continuance intention to use gamification for training in higher education: Integrating the technology acceptance model (TAM), social motivation, and task technology fit (TTF). *IEEE Access*, *8*, 21473–21484.	The TAM and TTF theories were used to construct a model that predicts lecturers' intention to continuously use the Moodle Gamification Training Platform.	*Perceived Usefulness, Attitudes, Task-Technology Fit Factors, Social Recognition, Social Influence, Perceived Ease of Use* affected *Continuance Use Intention* *Perceived Usefulness,* mediated *Social Recognition, Task-Technology Fit Factors, Perceived Ease of Use, Social Influence;* *Perceived Usefulness* affected *Continuance Use Intention* and *Task-Technology Fit Factors* affected *Perceived Ease of Use*
3	Dağhan, G., & Akkoyunlu, B. (2016). Modelling the continuance usage intention of online learning environments. *Computers in Human Behavior*, *60,* 198–211.	The TCT, ISS, COG and ECM theories were used to construct a model that predicts students' intention to continuously use an online learning environment.	*Information Quality, System Quality, Service Quality* affected *Confirmation* and *Information Quality, System Quality, Service Quality, Confirmation, Utilitarian Value,*

			Outcome Expectations, Perceived Value affected *Satisfaction*
4	Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, *45*, 359–374.	The TAM and ISS theories were used to construct a model that predicts students' intention to continuously use an online learning environment.	*Users' Intention, User Satisfaction* affected *Actual Use* *System Quality, Information Quality* affected *Users' Intention* *System Quality, Information Quality* affected *Satisfaction* and *Perceived Usefulness* mediated *Ease of Use, Users' Intention*
5	Pereira, F. A. D. M., Ramos, A. S. M., Gouvêa, M. A., & Da Costa, M. F. (2015). Satisfaction and continuous use intention of e-learning service in Brazilian public organisations. *Computers in Human Behavior*, *46*, 139–148.	The DED theory was used to construct a model that predicts students' intention to continuously use the online learning environment Moodle.	*Quality, Usability, Value, Value Disconfirmation* affected *Satisfaction* and *Satisfaction* affected *Continuance Use Intention*
6	Chang, C. C. (2013). Exploring the determinants of e-learning systems continuance intention in academic libraries. *Library Management*, *34*(1), 40–55.	The DED theory was used to construct a model that predicts students' intention to continuously use digital library systems.	*Web Quality* affected *Perceived Value, User Satisfaction* and *Perceived Value, Satisfaction* affected *Continuance Use Intention*
7	Lin, W. S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies*, *70*(7), 498–507.	The ECM and TTF theories were used to construct a model that predicts students' intention to continuously use a virtual learning system.	*Perceived Fit, Satisfaction* affected *Continuance Use Intention*

8	Limayem, M., & Cheung, C. M. K. (2011). Predicting the continued use of Internet-based learning technologies: The role of habit. *Behaviour and Information Technology*, *30*(1), 91–99.	The ECM was used to construct a model that predicts students' intention to continuously use the learning management system Blackboard.	*Habit* moderated *Information Systems Continuance Use Intention* and *Continuance Usage*
9	Lee, M. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model. *Computers and Education*, *54*(2), 506–516.	The ECM ,TAM, TPB and flow theories were used to construct a model that predicts students' intention to continuously use an OLE.	*Satisfaction, Perceived Usefulness, Attitude, Concentration, Subjective Norm, Perceived Behaviour Control* affected *Users' Continuous Use Intention*
10	Chiu, C. M., Sun, S. Y., Sun, P. C., & Ju, T. L. (2007). An empirical analysis of the antecedents of web-based learning continuance. *Computers and Education*, *49*(4), 1224–1245.	The STV and fairness theories were used to construct a model that predicts students' intention to continuously use a Unix Web-based learning programme.	*Attainment Value, Utility Value, Intrinsic Value, Distributive Fairness, Interactional Fairness* affected *Satisfaction* and *Utility Value, Satisfaction* affected *Continuous Use Intention*
11	Roca, J. C., Chiu, C. M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the technology acceptance model. *International Journal of Human-Computer Studies*, *64*(8), 683–696.	The TPB, TAM, and EDT theories were used to construct a model that predicts students' intention to continuously use an online learning environment.	*Satisfaction* affected *Continuance Use Intention* and *Perceived Usefulness, Information Quality, Confirmation, Service Quality, System Quality, Perceived Ease of Use, Cognitive Absorption* affected *Continuance Use Intention*
12	Limayem, M., Cheung, C., & Chan, G. (2003). Explaining information systems adoption and post-adoption: Toward an integrative model. *ICIS 2003 Proceedings*.	The TPB and ECM theories and the addition of the factor Habit were used to construct a model that predicts students' intention to continuously use the learning management system Blackboard.	*Initial Usage* affected *Continuance Usage* *Habit* moderated *Continuance Use Intention, Continuance Usage* and *Acceptance* affected *Continuance Decision, Usage factors*

4.3 Theories and potential factors extracted from literature sources

Of the 13 theories referenced by the selected literature sources, four contained potential factors that addressed students' intention to continuously use an OLE. These theories were the ISS theory from the information systems field and the ECM, expanded ECM, and flow theories from cognitive behavioural psychology. The ISS theory, developed by DeLone and McLean in 1992, who propose that a user's satisfaction with an information system is influenced by the quality of the system's information, the system's functionality, and the extent to which the user engages with the system. The ECM theory was developed from consumer behaviour by Bhattacherjee in 2001, and integrated theoretical aspects from the consumer behaviour expectation confirmation theory with IS usage. This adapted theory proposes that the decision of an IS user to continuously engage with an IS is similar to that of consumers who make repurchase decisions (Bhattacherjee, 2001). The IS-ECM theory, thus, states that users' intention to continuously use an IS is determined by their satisfaction, and the perceived usefulness of an IS. In 2006, Thong et al. expanded the IS-ECM theory (Bhattacherjee, 2001) to include two additional factors that address the ease of use and enjoyment of an IS, and referred to it as the expanded ECM theory. The flow theory was developed by Csikszentmihalyi in 1990 and is based on the concept of the flow state (Agarwal & Karahanna, 2000; Csikszentmihalyi, 1990). The flow theory states that people who feel in control of a task are attempting to reach a state of optimal experience by becoming totally immersed in the activity and failing to notice the passing of time. This theory is, thus, relevant, as it focuses on students' persistence to engage in the use of the SAM OLE, which is the main aspect of this study. These four theories together addressed nine potential factors that could predict students' intention to continuously use the SAM OLE. These potential factors were then used to construct a structural model for the assessment of students' intention to use the SAM OLE continuously. Table 4.2 lists the nine potential factors and their functions in the structural model.

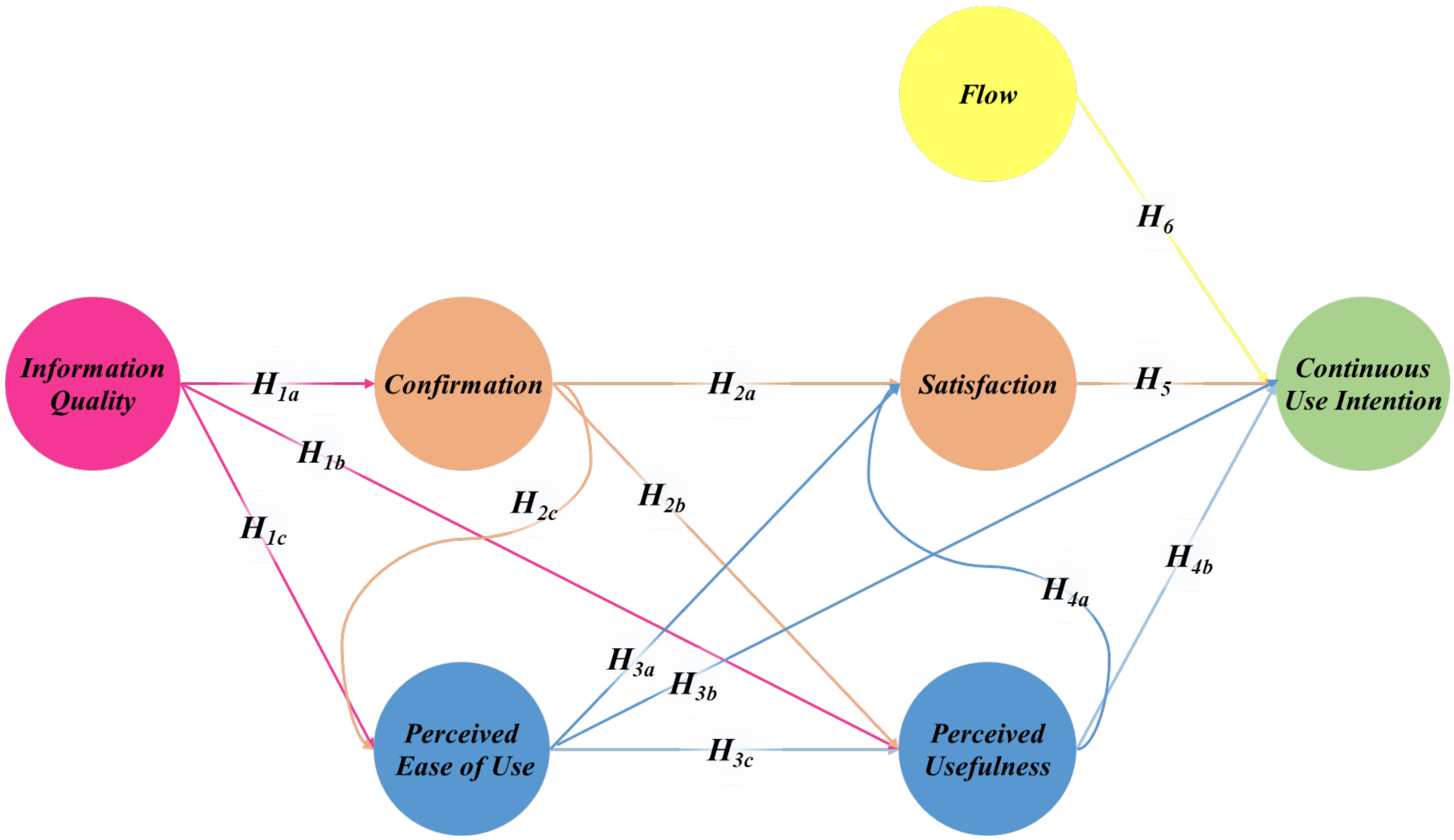
Table 4.2 *Relevant theories and functions of potential factors for the prediction of students' intention to continuously use the SAM OLE*

Theory	Potential factor extracted from theory	Functions of potential factor for the prediction of students' intention to continuously use the SAM OLE	Source
ISS	*Information Quality*	*Information Quality* predicts a user's response to the relevant, timely, accurate, and complete information output produced by the system or information within the system itself.	Lee (2010)
ECM	*Confirmation*	*Confirmation* determines the level at which a user perceives that their expectations of the information system are met.	Bhattacherjee (2001); Daɫhan and Akkoyunlu, (2016)
	Perceived Usefulness	*Perceived Usefulness* predicts the extent to which a user perceives that using an information system is worthwhile, handy and beneficial.	Bhattacherjee (2001); Daɫhan and Akkoyunlu, (2016)
	Satisfaction	*Satisfaction* predicts the extent of a user's emotions, that lead to the sensation of contentment as a result of the user's interaction with the information system.	Bhattacherjee (2001); Daɫhan and Akkoyunlu, (2016)
	Continuance Use Intention	*Continuance Use Intention* discerns a user's intention to continue using an information system.	Bhattacherjee (2001); Daɫhan and Akkoyunlu, (2016)
Expanded ECM	*Perceived Ease of Use*	*Perceived Ease of Use* predicts the extent to which a user perceives that using an information system does not require effort.	Davis (1989)
Flow	*Flow (Time Distortion, Immersion, Control*	*Time Distortion* predicts the level at which a user perceives temporal dissociation, or the inability to register the passage of time.	Agarwal and Karahanna (2000)
		Immersion predicts the level at which a user perceives focused immersion, or experiences total engagement in the use of an information system.	Agarwal and Karahanna (2000)
		Control predicts the level at which a user perceives being in charge and in control of an interaction with an information system.	Agarwal and Karahanna (2000)

4.4 Structural model of potential factors

The six potential factors that were extracted from the four appropriate theories were arranged in a structural model to predict students' intention to continuously use the SAM OLE. In this model, the six factors are depicted to influence the target factor, *Continuous Use Intention* (Figure 4.3 Structural model depicting the potential factors and relational hypotheses paths). The potential factor, *Information Quality* (indicated in pink in the structural model) that originated from the ISS theory (Daɫhan & Akkoyunlu, 2016; DeLone & McLean, 1992), is shown to have an indirect influence on *Continuous Use Intention* and was, thus, placed furthest from the target factor, to the left. The central area of the structural model consists of the five other potential factors (indicated in yellow, orange and blue). On the extreme right is the target factor that originated from the ECM (Bhattacherjee, 2001)and the expanded ECM (Thong et al., 2006) theories. The structural model, furthermore, indicates the respective research hypotheses (indicated by the letter '*H*'), represented by the bivariate relationships between the potential factors that influence *Continuous Use Intention*. The labels of the different hypotheses are delineated by alphanumeric subscripts. Each alphanumeric subscript contains a numeric value from one to six and a character of the alphabet, from *a* to *c*. The numeric value indicates the point of origin of each hypothesis: The point of origin is the independent potential factor in a bivariate relationship. The character of the alphabet is used to indicate the presence of more than one hypothesis, which originate from the same point of origin, or indicate multiple dependent potential factors. For example, from the *Perceived Ease of Use* potential factor, three different hypotheses arise, denoted as *H3a*, *H3b*, and *H3c*. In total, 13 relational hypotheses are indicated in the structural model.

Figure 4.3 *Structural model depicting the potential factors and relational hypotheses paths*



4.5 Relational hypotheses

After constructing the structural model, the paths between potential factors, with their respective relational hypotheses, were identified. Thirteen paths were identified, with their respective relational hypotheses. Each of these hypotheses was formulated for testing students' intention to continuously use the SAM OLE. The formulations and explanations of the 13 relational hypotheses of the structural model are depicted in Table 4.3.

Table 4.3 *Relational hypotheses and explanations of the structural model*

Hypothesis number	Hypothesis	Explanation	Structural model relationship
H_1a	*Information Quality* positively affects the *Confirmation* (of expectation) of the SAM OLE	This hypothesis posits that the quality of the information provided by the SAM OLE confirms the expectations of a user of the SAM OLE.	Information Quality → Confirmation
H_1b	Information Quality positively affects Perceived Usefulness of SAM OLE	This hypothesis posits that the quality of the information provided by the SAM OLE is deemed useful to a user of the SAM OLE.	Information Quality → Perceived Usefulness
H_1c	Information Quality positively affects Perceived Ease of Use of the SAM OLE	This hypothesis posits that the quality of the information provided by the SAM OLE facilitates the ease with which a user is able to use the SAM OLE.	Information Quality → Perceived Ease of Use
H_2a	*Confirmation* (of expectation) positively affects the *Satisfaction* with the SAM OLE	This hypothesis posits that a user's expectations were satisfied when they used the SAM OLE.	Confirmation → Satisfaction
H_2b	*Confirmation* (of expectation) positively affects *Perceived Usefulness* of the SAM OLE	This hypothesis posits that a user's expectations of usefulness of the SAM OLE were met.	Confirmation → Perceived Usefulness

H_2c	*Confirmation* (of expectation) positively affects *Perceived Ease of Use* of the SAM OLE	This hypothesis posits that a user's expectations of the ease of use of the SAM OLE were met.	Confirmation → Perceived Ease of Use
H_{3a}	*Perceived Ease of Use* positively affects *Satisfaction* with the SAM OLE	This hypothesis posits that a user's ease of use of the SAM OLE influences their satisfaction with the SAM OLE	Perceived Ease of Use → Satisfaction
H_3a	Perceived Ease of Use positively affects Continuous Use Intention of use of the SAM OLE	This hypothesis posits that a user's ease of use of the SAM OLE encourages a user to continuously use the SAM OLE.	Perceived Ease of Use → Continuous Use Intention
H_3b	Perceived Ease of Use positively affects Perceived Usefulness in the SAM OLE	This hypothesis posits that a user's ease of use of the SAM OLE influences their perception of the usefulness of the SAM OLE.	Perceived Ease of Use → Perceived Usefulness
H_4a	*Perceived Usefulness* positively affects *Satisfaction* with the SAM OLE	This hypothesis posits that a user's perception of usefulness of the SAM OLE influences their satisfaction with the SAM OLE.	Perceived Usefulness → Satisfaction
H_4b	Perceived Usefulness positively affects the Continuous Use Intention of the SAM OLE.	This hypothesis posits that a users' perception of usefulness of the SAM OLE encourages them to continue to use the SAM OLE.	Perceived Usefulness → Continuous Use Intention
H_5	Satisfaction positively affects the Continuous Use Intention of the SAM OLE	This hypothesis posits that a satisfied user will be encouraged to continue to use the SAM OLE.	Satisfaction → Continuous Use Intention
H_6	*Flow* positively affects the *Continuous Use Intention* of the SAM OLE	This hypothesis posits that an immersed and deeply engaged user will be encouraged to continue to use the SAM OLE.	Flow → Continuous Use Intention

4.6 Summary

A structural model was constructed, based on a comprehensive review of the literature. After scrutinising 65 literature sources, 12 were deemed suitable for identifying relevant theories and for extracting potential factors that could influence students' intention to continuously use the SAM OLE. The four theories – ISS theory of the information systems field, the ECM, expanded ECM and flow theories of the field of cognitive behavioural psychology – underpinned the understanding of students' intention to continuously use the SAM OLE. The literature was, furthermore, also used to extract six relevant potential factors that had the potential to influence the target factor *Continuous Use Intention*. The six factors, together with the target factor, were arranged in a structural model that could be assessed to identify those potential factors that did influence *Continuous Use Intention*. Thirteen path relationships were identified in the structural model, which formed the foundation of the formulation of 13 relational hypotheses. These hypotheses were ultimately tested using SEM to identify the actual factors amongst the potential factors that influenced students' intention to continuously use the SAM OLE.

Chapter 5

Validation of the measurement models

5.1 Introduction

In the second phase of this study, measurement models were specified and validated before the structural model could be assessed. In order to enable the specification of measurement models, a questionnaire was developed as a measurement instrument and is referred to as the MIQ. The MIQ was developed to measure the potential factors and the target factor in the structural model. This was achieved by devising questionnaire items (indicators), which acted as observable variables, to measure the potential factors and the target factor. Before the measurement models could be applied to identify factors that influenced students' intention to continuously use the SAM OLE, the models were, first, assessed for their reliability and validity. Therefore, the sub-question that was answered in Phase 2 is:

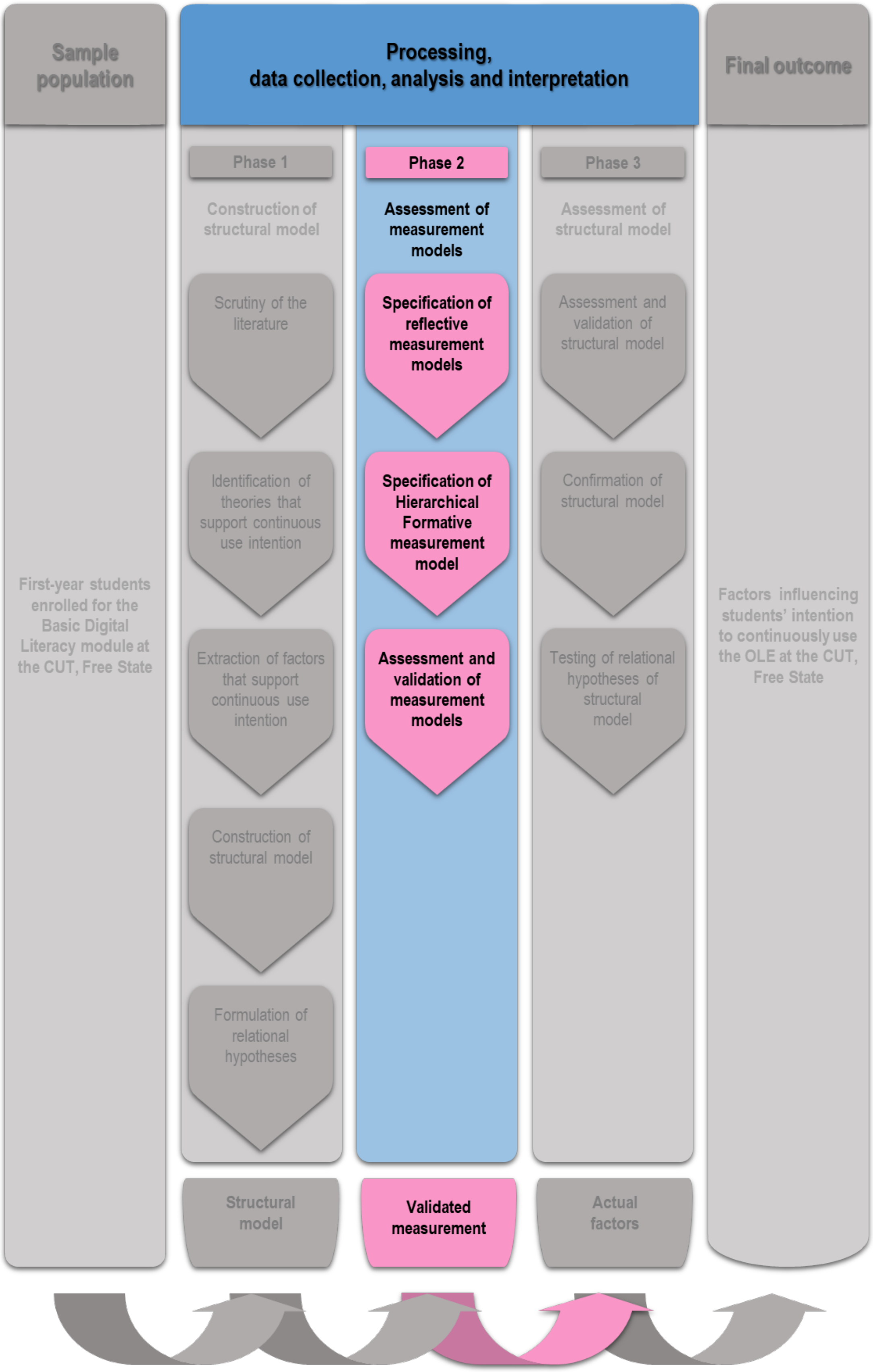
> *Which indicators of the measurement models can be used to measure the potential factors that influence students' intention to continuously use the SAM OLE?*

In order to answer the research sub-question, the following actions were undertaken:

1. Reflective or formative indicators of the potential factors and the target factor were specified.
2. An MIQ containing reflective and formative indicators was developed to measure the potential factors and the target factor.
3. The MIQ was administered to the student population and the data were captured.
4. The validity and reliability of the measurement models were determined.

Figure 5.1 *depicts how Phase 2 relates to the other components in the conceptual framework of this study.*

Figure 5.1 *Conceptual framework depicting objectives of the different phases, highlighting Phase 2*



5.2 Items of the MIQ

5.2.1 Biographical and supplemental items

The MIQ comprised 45 items, of which ten were dedicated to obtaining biographical and supplemental information about students. The first five items probed for biographical information, school subjects and details about university enrolment (Table 5.1). The subsequent five items were dedicated to eliciting information about students' prior experience of and engagement with the SAM OLE, as well as their access to computers or smartphones. To ensure that the study population was uniform, item 4 was included to ascertain whether students had gained knowledge of basic digital literacy during secondary education; consequently, students who indicated that they had taken the subjects computer-aided technology (CAT) and information technology (IT) at school were excluded from the study. Similarly, item 9 was included to obtain information about student engagement with the SAM OLE. The data of students who indicated that they did not engage with the SAM OLE were removed from the data set during data screening.

Table 5.1 *Biographical and supplemental items of the MIQ*

Item No.	Item	Item option
Biographical and related items		
1.	Mark the appropriate interval for your age	18 – 20, 21 – 23, 24 – 26, 27+
2.	Gender	Female, Male, Other
3.	Home Language	Afrikaans, English, Ndebele, Northern Sotho, Sotho, Swati, Tsonga, Tswana, Venda, Xhosa, Zulu, Other
4.	Did you take one of the following subjects (or similar) at school?	Computer-aided technology (CAT), Information technology (IT) or Neither of the above
5.	In which qualification are you enrolled?	Engineering, Accountancy, Internal Auditing, Agriculture, Community Development Work, Environmental Health, Education, Somatology, Tourism Management, Radiography, Design and Studio Art, Biomedical Technology, Clinical Technology, Financial Information Systems, Public Management, Economics and Management, Marketing, Human Resources Management

Supplemental related items		
6.	Do you own a computer?	Yes/No
7.	Do you own a smartphone?	Yes/No
8.	How many semesters have you engaged with SAM OLE for your studies?	One, two, three, four, more than four
9.	How regularly did you engage with SAM OLE during a normal academic week, on average?	Not at all, Less than once a week, about once a week, Two or three times a week, More than three times a week.
10.	How much time, on average, in a normal academic week, did you engage with SAM OLE?	Less than 30 minutes, Between 31 and 60 minutes, Between 61 and 90 minutes, More than 90 minutes

5.2.2 Reflective measurement indicators

The MIQ comprised reflective indicators for five of the potential factors and the target factor (*Continuous Use Intention*). Table 5.2 depicts the respective reflective indicators that were developed for the structural model.

Table 5.2 *Reflective measurement indicators of the MIQ*

Potential factor	Item code	Item
	CF1	My experience with using SAM was better than what I expected.
Confirmation	CF2	The service level provided by SAM was better than what I expected.
	CF3	Overall, most of my expectations from using SAM were confirmed.
	CUI1	I intend to continue using SAM rather than discontinue its use.
Continuous Use Intention	CUI2	My intentions are to continue using SAM rather than using any alternative means.
	CUI3	I will use the e-learning system on a regular basis in the future.
	IQ1	SAM provides correct and accurate information.

Information Quality	IQ2	SAM provides complete and sufficient information.
	IQ3	SAM provides precise and clear information.
	IQ4	The information provided by the SAM meets my needs.
	IQ5	The information provided by the SAM helps to solve my problems.
Perceived Ease of Use	PEOU1	Learning how to use SAM is easy for me.
	PEOU2	My interaction with SAM is clear and understandable.
	PEOU3	I find SAM easy to use.
	PEOU4	It is easy for me to become skilful at using SAM.
Perceived Usefulness	PU1	Using SAM can improve my learning performance.
	PU2	Using SAM can increase my learning effectiveness.
	PU3	I find SAM to be useful to me.
	PU4	Using SAM increases my learning productivity
Satisfaction	S1	Using SAM is enjoyable.
	S2	Using SAM is pleasurable.
	S3	I am pleased with the experience of using SAM.
	S4	I am delighted with the experience of using SAM.

5.2.3 Formative measurement indicators

In addition to the potential factors with reflective indicators of this study, one potential factor with formative indicators was developed. This potential factor, *Flow,* comprised three higher-order potential factors, each with a set of three to five indicators, which amounted to 12 indicators. The three higher-order potential factors of *Flow* were *Time Distortion*, *Control,* and *Immersion*. Table 5.3 depicts the indicators associated with the three higher-order potential factors of *Flow*.

Table 5.3 *Formative measurement indicators of the MIQ*

Higher-order potential factor	Item code	Item
	TD1	Time appears to go by very quickly when I am using SAM.
	TD2	Sometimes I lose track of time when I am using SAM.
Time Distortion	TD3	Time flies when I am using the SAM.
	TD4	I end up spending more time than I had planned on SAM.
	TD5	I often spend more time on SAM than I had intended.
	CT1	When using SAM, I feel in control.
Control	CT2	I feel that I have control over my interaction with SAM.
	CT3	SAM allows me to control my computer interaction.
	I1	I become unaware of my surroundings while using SAM.
Immersion	I2	I temporarily forget worries about everyday life while using SAM.
	I3	While using SAM, I am able to block out most other distractions.
	I4	While using SAM, I am immersed in the task I am performing.

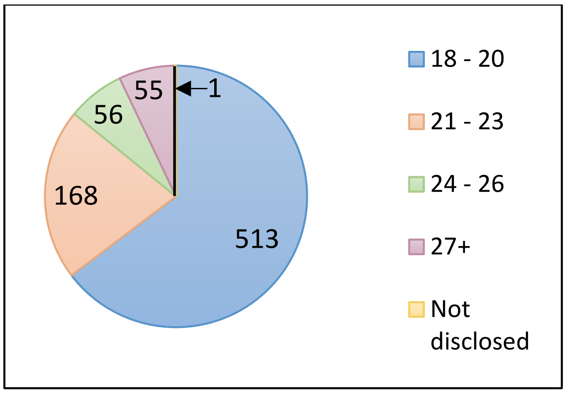
5.3 Summary statistics of biographical and supplemental information

More than 2000 students were enrolled in the Basic Digital Literacy module; of whom 1003 completed the MIQ. After applying the exclusion criteria, the data of 210 of the students were removed from the data set. Thus, 793 students made up the sample of this study.

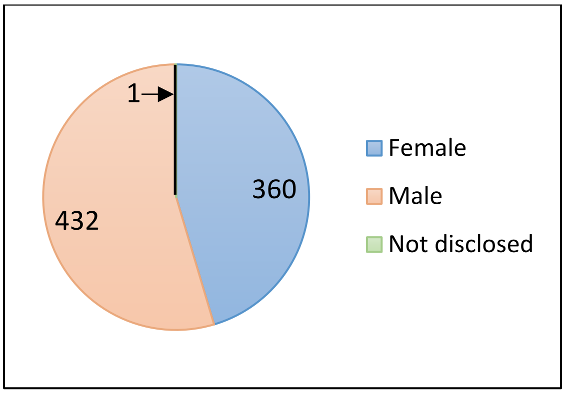
5.3.1 Biographical information

The students who chose to respond to the MIQ were a diverse group of participants in terms of age, gender, home language and qualification enrolled for. The majority of the students (65%) were aged between 18 and 20 years (Figure 5.2A). Each of the other age categories contained fewer than 25% of the students of the sample. The gender distribution was relatively equal, with male students making up approximately 55% of the student population and female students approximately 45% (Figure 5.2B). More than 50% of the participating students were Sotho-speaking (Figure 5.2C). Fewer than 15% of the participating students comprised each of the other language categories. In this study, approximately 49% of the participating students were enrolled in the Faculty of Engineering, Built Environment and Information, while the remainder of the students were distributed amongst the other three faculties (Figure 5.2D).

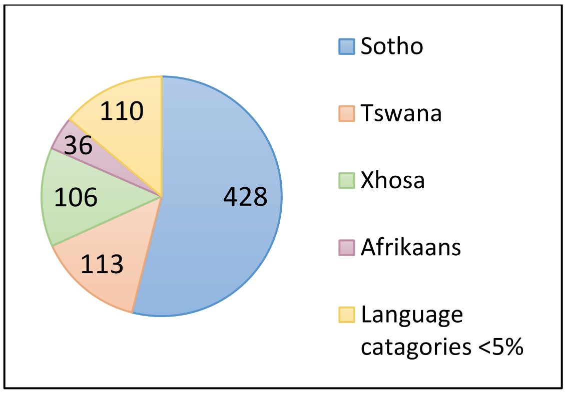
Figure 5.2 *Graphs of biographical information A. Ages of participants. B. Gender of participants. C. Home languages of participants. D. Faculties students were enrolled in*



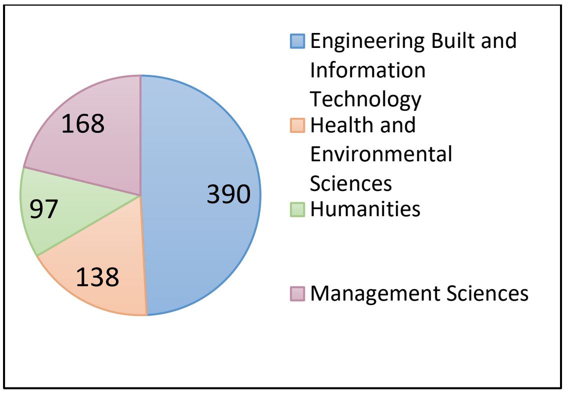
A.



B.



C.

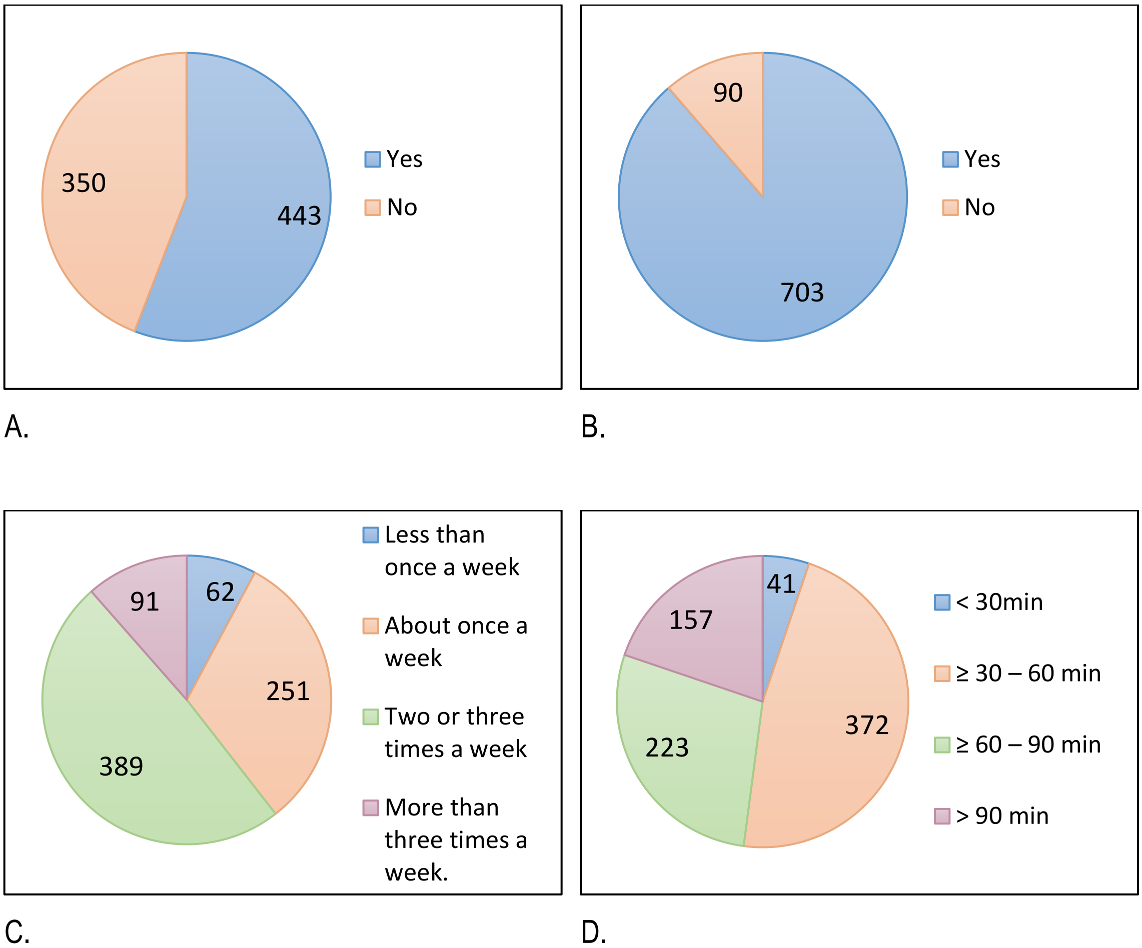


D.

5.3.2 Supplemental information

Supplemental information of the student participants was elicited on their access to computers and smartphones, as well as the duration of engagement with the SAM OLE. Student access to computers and smartphones varied widely (Figure 5.3A, B). More than 85% of the students had access to smartphones, while approximately 56% of the students had access to computers. For the 12-week duration of the module, more than 80% of the students engaged with the SAM OLE one to three times a week, whereas fewer than 15% of the students engaged more than three times a week (Figure 5.3C). Nearly half the student participants engaged with the SAM OLE for an hour or more, while 10% of the students engaged for less than 30 minutes at a time (Figure 5.3D).

Figure 5.3 *Graphs of supplemental information. A. Participants' computer access. B. Participants' smartphone access. C. Participants' engagement with SAM OLE per week. D. Duration of participants' engagement with the SAM OLE*



5.3.3 Reflective indicator summary statistics

The summary statistics of the reflective indicators indicate a relatively uniform pattern across the 23 indicators of the potential factors and target factor in the structural model. More than 50% of the student population strongly agreed or agreed (selected indicator values of 7 or 6 on the 7-point scale) with the statements relating to all the potential factors. The combined percentage of students who strongly agreed or agreed with the statements relating to all the potential factors ranged from approximately 55% of the students for the target factor *Continuous Use Intention* (CUI2), to approximately 83% for the potential factor *Perceived Usefulness* (PU3). For all indicators of potential factors, a relatively low percentage of students strongly disagreed or disagreed with the statements relating to the factors (selected indicator values of 1 and 2). For most indicators, fewer than 12% of the participants were undecided about statements related to the potential factors. **Table 5.4** depicts the numbers and percentages of participant selections of the different values for the indicators of the reflectively measured potential factors.

Table 5.4 *Numbers and percentages of values of the indicators of the reflectively measured factors*

	Confirmation			*Perceived Usefulness*			
Indicator	**CF1**	**CF2**	**CF3**	**PU1**	**PU2**	**PU3**	**PU4**
Likert Scale	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**
Strongly disagree 1	36 (4.5)	18 (2.3)	33 (4.2)	21 (2.6)	17 (2.1)	18 (2.3)	23 (2.9)
Disagree 2	24 (3.0)	24 (3.0)	32 (4.0)	10 (1.3)	15 (1.9)	14 (1.8)	12 (1.5)
Somewhat disagree 3	34 (4.3)	22 (2.8)	44 (5.5)	19 (2.4)	14 (1.8)	12 (1.5)	17 (2.1)
Undecided 4	76 (9.6)	85 (10.7)	95 (12.0)	49 (6.2)	47 (5.9)	25 (3.2)	60 (7.6)
Somewhat agree 5	94 (11.9)	99 (12.5)	134 (16.9)	71 (9.0)	63 (7.9)	67 (8.4)	91 (11.5)
Agree 6	219 (27.6)	213 (26.9)	247 (31.1)	196 (24.7)	191 (24.1)	174 (21.9)	209 (26.4)
Strongly agree 7	310 (39.1)	332 (41.9)	208 (26.2)	427 (53.8)	446 (56.2)	483 (60.9)	381 (48.0)
Total	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)

n. = number of student responses

	Information Quality					*Satisfaction*			
Indicator	**IQ1**	**Q2**	**IQ3**	**IQ4**	**IQ5**	**S1**	**S2**	**S3**	**S4**
Likert Scale	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**
Strongly disagree 1	9 (1.1)	15 (1.9)	18 (2.3)	14 (1.8)	36 (4.5)	29 (3.7)	44 (5.5)	19 (2.4)	22 (2.8)
Disagree 2	9 (1.1)	18 (2.3)	11 (1.4)	36 (4.5)	30 (3.8)	25 (3.2)	39 (4.9)	23 (2.9)	25 (3.2)
Somewhat disagree 3	21 (2.6)	22 (2.8)	26 (3.3)	23 (2.9)	46 (5.8)	24 (3.0)	26 (3.3)	12 (1.5)	22 (2.8)
Undecided 4	45 (5.7)	53 (6.7)	54 (6.8)	81 (10.2)	87 (11.0)	61 (7.7)	90 (11.3)	53 (6.7)	76 (9.6)
Somewhat agree 5	63 (7.9)	69 (8.7)	78 (9.8)	104 (13.1)	124 (15.6)	118 (14.9)	118 (14.9)	89 (11.2)	90 (11.3)
Agree 6	204 (25.7)	187 (23.6)	251 (31.7)	196 (24.7)	198 (25.0)	180 (22.7)	235 (29.6)	228 (28.8)	210 (26.5)
Strongly agree 7	442 (55.7)	429 (54.1)	355 (44.8)	339 (42.7)	272 (34.3)	356 (44.9)	241 (30.4)	369 (46.5)	348 (43.9)
Total	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)

n. = number of student responses

	Perceived Ease of Use				*Continuous Use Intention*		
Indicator	**PEOU1**	**PEOU2**	**PEOU3**	**PEOU4**	**CUI1**	**CUI2**	**CUI3**
Likert Scale	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**	**n (%)**
Strongly disagree 1	36 (4.5)	34 (4.3)	46 (5.8)	11 (1.4)	54 (6.8)	48 (6.1)	41 (5.2)
Disagree 2	47 (5.9)	28 (3.5)	42 (5.3)	16 (2.0)	21 (2.6)	38 (4.8)	34 (4.3)
Somewhat disagree 3	45 (5.7)	33 (4.2)	47 (5.9)	9 (1.1)	24 (3.0)	43 (5.4)	24 (3.0)
Undecided 4	54 (6.8)	83 (10.5)	68 (8.6)	48 (6.1)	97 (12.2)	134 (16.9)	124 (15.6)
Somewhat agree 5	119 (15.0)	106 (13.4)	122 (15.4)	84 (10.6)	78 (9.8)	88 (11.1)	101 (12.7)
Agree 6	205 (25.9)	243 (30.6)	200 (25.2)	192 (24.2)	209 (26.4)	184 (23.2)	158 (19.9)
Strongly agree 7	287 (36.2)	266 (33.5)	268 (33.8)	433 (54.6)	310 (39.1)	258 (32.5)	311 (39.2)
Total	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)

n. = number of student responses

5.3.4 Formative indicator summary statistics

Like the reflective indicators, the summary statistics of the formative indicators also displayed a relatively uniform pattern across the 12 indicators of the higher-order potential factor, *Flow*. For 10 of the 12 indicators of the lower-order potential factors *Immersion*, *Time Distortion* and *Control*, more than 50% of the participating students strongly agreed or agreed (selected indicator values of 6 or 7) with the statements relating to these lower-order potential factors. In contrast to the reflective indicators, more students expressed some or other form of disagreement with the statements presented for the lower-order potential factors. In particular, up to 35% of the students were in disagreement with one of the *Immersion* indicators (I1). The percentage of students who were undecided about the statements related to the potential factors ranged from about 7% to 16%, which was marginally greater than what was observed for the reflectively measured potential factors. For most indicators, fewer than 12% of the students were undecided about statements related to the potential factors. Table 5.5 depicts the numbers and percentages of student selected values for the different indicators of the formatively measured potential factors.

Table 5.5 *Number and percentages of values for the indicators of the formatively measured factors*

	Immersion				*Time Distortion*					*Control*		
Indicator	I1	I2	I3	I4	TD1	TD2	TD3	TD4	TD5	CT1	CT2	CT3
Likert Scale	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Strongly disagree1	123 (15.5)	112 (14.1)	53 (6.7)	42 (5.3)	57 (7.2)	72 (9.1)	66 (8.3)	56 (7.1)	72 (9.1)	39 (4.9)	34 (4.3)	22 (2.8)
Disagree 2	103 (13.0)	99 (12.5)	57 (7.2)	37 (4.7)	48 (6.1)	57 (7.2)	51 (6.4)	65 (8.2)	59 (7.4)	41 (5.2)	45 (5.7)	26 (3.3)
Somewhat disagree 3	56 (7.1)	46 (5.8)	50 (6.3)	31 (3.9)	30 (3.8)	38 (4.8)	40 (5.0)	40 (5.0)	46 (5.8)	40 (5.0)	51 (6.4)	25 (3.2)
Undecided 4	130 (16.4)	115 (14.5)	105 (13.2)	123 (15.5)	59 (7.4)	73 (9.2)	72 (9.1)	79 (10.0)	71 (9.0)	106 (13.4)	107 (13.5)	72 (9.1)
Somewhat agree 5	112 (14.1)	95 (12.0)	107 (13.5)	149 (18.8)	89 (11.2)	90 (11.3)	77 (9.7)	114 (14.4)	104 (13.1)	127 (16.0)	148 (18.7)	111 (14.0)
Agree 6	125 (15.8)	113 (14.2)	178 (22.4)	215 (27.1)	174 (21.9)	167 (21.1)	163 (20.6)	162 (20.4)	169 (21.3)	187 (23.6)	194 (24.5)	216 (27.2)
Strongly agree 7	144 (18.2)	213 (26.9)	243 (30.6)	196 (24.7)	336 (42.4)	296 (37.3)	324 (40.9)	277 (34.9)	272 (34.3)	253 (31.9)	214 (27.0)	321 (40.5)
Total	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)	793 (100)

5.4 Validity and reliability of reflective measurement models

Prior to measuring the structural model, the measurement models were, first, assessed for their validity and reliability in terms of several validation measures, to ensure that the indicators belonging to each of the potential factors in the structural model were reliable and valid measures of the potential factors. These measures were convergent validity, discriminant validity and internal consistency reliability.

5.4.1 Convergent validity

Convergent validity indicates the extent to which a reflective indicator correlates positively with alternative reflective indicators of the same potential factor. Two criteria of convergent validity – indicator outer loadings and AVE – were calculated for the reflectively measured potential factors. The outer loading values of all the reflective indicators were greater than the threshold value of 0.7, showing that the indicators in a set belonging to a potential factor demonstrate a high level of interchangeability or commonality (Table 5.6). Similarly, the observed AVE values were also greater than the threshold value of 0.5. These criteria, thus, demonstrate that the reflective indicators of the different sets all possess convergent validity.

Table 5.6 *Indicator outer loadings and AVE values for each potential factor and target factor*

Indicator		Factor	Indicator outer loading	AVE
CF1			0.842	
CF2	►	*Confirmation*	0.797	0.629
CF3			0.737	
CUI1			0.851	
CUI2	►	*Continuous Use Intention*	0.834	0.697
CUI3			0.819	
IQ2			0.715	
IQ3	►	*Information Quality*	0.731	0.522
IQ4			0.722	
IQ5			0.723	
PEOU1			0.781	
PEOU2	►	*Perceived Ease of Use*	0.806	0.592
PEOU3			0.764	
PEOU4			0.723	
PU1			0.776	
PU2	►	*Perceived Usefulness*	0.759	0.595
PU3			0.704	
PU4			0.840	
S1	►	*Satisfaction*	0.831	0.611

S2	0.789
S3	0.762
S4	0.842

5.4.2 Discriminant validity

Discriminant validity measures were calculated to indicate how distinct a set of indicators of a particular reflective measurement model was compared to other measurement models. The three discriminant validity criteria – cross loadings, the Fornell-Larcker criterion and the HTMT criterion – were, thus, calculated to determine how distinct the different sets of indicators of the measurement models were. When viewing the cross loadings of all the indicator sets, the cross loadings of the indicators related to a particular potential factor were substantially greater than the indicator sets of other potential factors (Table 5.7). These observed cross loadings confirm that the different indicator sets of all the potential factors were distinct.

Table 5.7 *Outer loading values for each indicator cross-loaded on their associated potential factor and target factor*

Indicator	Potential factors and target factor					
	Confirmation	*Continuous Use Intention*	*Information Quality*	*Perceived Ease of Use*	*Perceived Usefulness*	*Satisfaction*
CF1	0.842	0.471	0.526	0.570	0.565	0.606
CF2	0.797	0.433	0.483	0.519	0.503	0.546
CF3	0.737	0.293	0.408	0.470	0.426	0.499
CUI1	0.484	0.851	0.483	0.405	0.538	0.540
CUI2	0.425	0.834	0.443	0.354	0.473	0.470
CUI3	0.362	0.819	0.417	0.260	0.489	0.464
IQ2	0.408	0.387	0.715	0.347	0.465	0.410
IQ3	0.440	0.396	0.731	0.422	0.439	0.425
IQ4	0.424	0.400	0.722	0.372	0.478	0.491
IQ5	0.457	0.372	0.723	0.452	0.503	0.495
PEOU1	0.491	0.252	0.407	0.781	0.353	0.450
PEOU2	0.545	0.339	0.447	0.806	0.465	0.538

PEOU3	0.489	0.255	0.402	0.764	0.339	0.466
PEOU4	0.492	0.393	0.439	0.723	0.497	0.487
PU1	0.447	0.525	0.522	0.369	0.776	0.469
PU2	0.453	0.413	0.440	0.356	0.759	0.498
PU3	0.519	0.408	0.554	0.466	0.704	0.614
PU4	0.521	0.501	0.489	0.476	0.840	0.606
S1	0.572	0.479	0.525	0.519	0.587	0.831
S2	0.540	0.459	0.492	0.499	0.536	0.789
S3	0.550	0.449	0.481	0.563	0.603	0.762
S4	0.512	0.457	0.475	0.394	0.501	0.741

Discriminant validity was also measured, by calculating the Fornell-Larcker criterion, a derivative of the AVE. According to the Fornell-Larcker criterion, the square root values of the AVE (indicated with grey shading) are all greater than correlations between the different potential factors (Table 5.8). Thus, the Fornell-Larcker criterion also supports the notion that the different indicator sets of all the potential factors are distinct.

Table 5.8 *Fornell-Larcker criterion values (indicated in grey) and potential factor correlations*

Potential factor	**Potential factor**					
	Confirmation	***Continuous Use Intention***	***Informatio n Quality***	***Perceived Ease of Use***	***Perceived Usefulness***	***Satisfaction***
Confirmation	0.793					
Continuous Use Intention	0.510	0.835				
Information Quality	0.599	0.537	0.723			
Perceived Ease of Use	0.658	0.409	0.554	0.769		
Perceived Usefulness	0.632	0.600	0.653	0.546	0.771	
Satisfaction	0.696	0.590	0.632	0.635	0.714	0.781

The HTMT ratio, which is considered a more reliable approach to determining discriminant validity than calculating cross loadings and the Fornell-Larcker criterion, was also calculated. All calculated HTMT ratios were less than 1, which confirms discriminant validity (Table 5.9). Together with the calculations of the cross loadings and the Fornell-Larcker criterion values, these observations show that the set of indicators of the different reflective measurement models are all distinctly different.

Table 5.9 *HTMT ratio values for the different potential factors*

Potential factor	**Potential factor**					
	Confirmation	***Continuous Use Intention***	***Information Quality***	***Perceived Ease of Use***	***Perceived Usefulness***	***Satisfaction***
Confirmation						
Continuous Use Intention	0.674					
Information Quality	0.848	0.727	0.757			
Perceived Ease of Use	0.886	0.515	0.660	0.748		
Perceived Usefulness	0.848	0.770	0.819	0.887	0.691	
Satisfaction	0.931	0.750	0.817	0.851	0.807	0.909

5.4.3 Internal consistency reliability

Internal consistency reliability was measured using the two criteria Cronbach α and composite reliability. The PLS algorithm was executed in SmartPLS to compute these two estimates for each set of potential factor indicators, to determine whether the indicators in the set demonstrated high levels of average inter-correlations. The calculated Cronbach α values for each indicator set are close to or greater than the threshold value of .7, indicating internal consistency reliability for all indicator sets (Table 5.10). The less conservative estimate of internal consistency, composite reliability, indicates values in the order of .8, which is substantially greater than the threshold value of .7. Thus, both the Cronbach α and composite reliability values strongly support the notion that the indicators in the different potential factor sets are internally consistent.

Table 5.10 *Cronbach α and composite reliability values for establishing internal consistency reliability*

Potential factor	Cronbach α	Composite reliability
Confirmation	.705	.835
Continuous Intention	.783	.873
Information Quality	.712	.837
Perceived Ease of Use	.696	.814
Perceived Usefulness	.770	.853
Satisfaction	.771	.854

5.5 Validity of the formative measurement models

Once the reflective measurement models had been validated, the higher-order formative measurement model was also validated. The formative measurement model was assessed in terms of collinearity, significance, and relevance of outer weights, to ensure that each indicator set belonging to a particular potential factor in the structural model was a valid measure of the potential factors.

5.5.1 Collinearity between formative indicators

Collinearity amongst the formative indicators belonging to the potential factor *Flow* in the formative measurement model was assessed with the VIF. The VIF estimates the amount of multicollinearity that exists amongst a set of formative indicators. The calculated VIF estimates for the three lower-order potential factors, *Control*, *Immersion* and *Time Distortion*, were all substantially lower than the threshold value of 3. These estimates confirm that multicollinearity was not an issue with this measurement model. Table 5.11 depicts the VIF estimates for the formative measurement model.

Table 5.11 *Variable inflation factor scores*

Potential factor	Higher-order potential factor	Outer VIF value
	Control	1.528
Flow	*Immersion*	1.629
	Time Distortion	1.250

5.5.2 Significance and relevance of outer weights

The outer weights of the lower-order potential factor indicator sets and their contribution to their associated potential factors were calculated. The significance and relevance of these outer weights were measured by calculating the *t*-statistic for each indicator set. The outer weights of each set of the three lower-order potential factors, *Control*, *Immersion* and *Time Distortion*, were all significant at a 5% significance level (α = 0.05). These data, thus, reveal that the indicators in a set make a significant contribution to their associated lower-order potential factors. Table 5.12 depicts the outer weights and statistical analyses of the indicator sets of the lower-order potential factors of the formative measurement model.

Table 5.12 *Significance of outer weights*

Higher-order potential factor	Lower-order potential factor	Outer weight	Sample mean	Standard deviation	t Value	p Value
	Control	0.507	0.507	0.021	23.681	< .001
Flow	*Immersion*	0.417	0.417	0.017	24.393	< .001
	Time Distortion	0.317	0.316	0.024	13.123	< .001

5.6 Summary

In this phase of the study, the measurement models were successfully specified and validated, and can thus, be applied to the assessment of the structural model. For the assessment of the structural model, several measurement models were specified by constructing a MIQ that comprised indicators that were used to measure the potential factors and target factor in the structural model. The validation data of the measurement models were gathered from the MIQ, which was completed by 793 student participants. The participating students were mostly Sotho-speaking, younger than 20 years and enrolled in the Faculty of Engineering, Built Environment and Information. Most of these students had access to smartphones or computers, thus, enabling them to engage with the SAM OLE at least two or three times a week for up to 60 minutes per session. The validity and reliability of the reflective measurement models were supported by the calculations of the three estimates, namely convergent validity, discriminant validity and internal consistency reliability. Similarly, the higher-order formative measurement model was validated by assessing collinearity and determining the significance and relevance of the outer weights. These results, thus, permit the assessment of the structural model to identify the actual factors amongst the potential factors that influence students' intention to continuously use the SAM OLE.

Chapter 6

Actual factors that influence students' engagement with the skills assessment manager online learning environment

6.1 Introduction

In the third phase of this study, the structural model was assessed, to identify the actual factors that predict students' intention to continuously use the SAM OLE. In order to ensure that the actual factors were reliably obtained, the structural model was first assessed for collinearity amongst the potential factors and target factor (*Continuous Use Intention*). After establishing that no collinearity existed amongst the potential factors and target factor, the relational hypotheses were tested. Therefore, the sub-question that was answered in Phase 3 was:

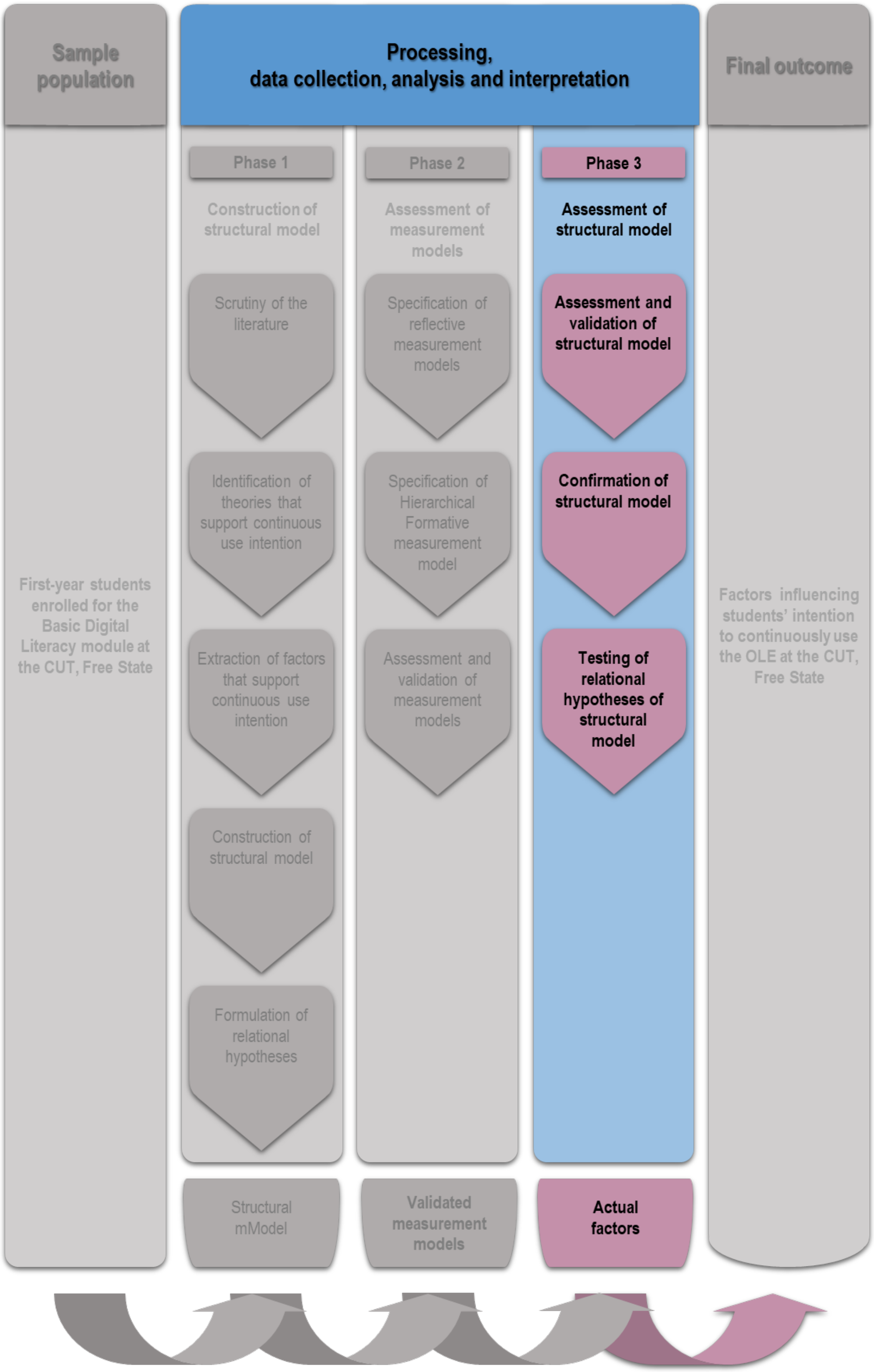
> *Which of the potential factors are actual factors that influence students' intention to continuously use the SAM OLE?*

In order to answer this sub-research question, the following actions were undertaken:

1. The structural model was assessed to determine if collinearity existed amongst the potential factors and target factor.
2. Thereafter, the structural model was assessed to identify the actual factors that predict students' intention to continuously use the SAM OLE.

Figure 6.1 depicts how Phase 3 relates to the other components of the conceptual framework of this study.

Figure 6.1 *Conceptual framework depicting objectives of the different phases, highlighting Phase 3*



6.2 Collinearity between factors

Prior to assessing the properties of the structural model, the model was, first, assessed to ascertain whether collinearity issues existed between the potential factors and target factor in the model. Because the coefficients, which were calculated for the relationships between the independent and dependent potential factors, were derived from estimating regression equations, the point estimates and standard errors may be biased because of strong correlations between factor pairs. Therefore, the potential existence of such strong correlations between potential factors would necessitate an assessment of whether collinearity existed amongst the potential factors and target factor (Hair et al., 2021). Collinearity between the different paths connecting potential factors of the structural model was determined by calculating the VIF value for each path (Table 6.1). The VIF values indicate that collinearity is not an issue in this study, because all the values are below the critical collinearity threshold value of 3.

Table 6.1 *Collinearity VIF values for potential factor paths in the structural model*

	Dependent factor				
Independent Factor	***Confirmation***	***Continuous Use Intention***	***Information Quality***	***Perceived Usefulness***	***Satisfaction***
Confirmation	-	-	-	2.050	2.170
Continuous Use Intention[1]	-	-	-		
Flow	-	1.902	-		
Information Quality	1.000	-	-	1.677	
Perceived Ease of Use	-	1.773	-	1.895	1.854
Perceived Usefulness	-	2.298	-		1.753
Satisfaction	-	2.650	-		

[1] Target factor

6.3 Relationships of structural model

After establishing that no collinearity issues existed between the potential factors and the target factor in the structural model, the relational hypotheses that describe the relationships between potential factors and the target factor were tested. The significance of the path coefficients was determined through Bootstrapping and the calculation of t values, while the relevance of the path coefficients are described in terms of the strength of the relationships between the potential factors and the target factor. Based on the t value, 12 of the 13 relational hypotheses are supported at a 5% significance level (α = 0.05). The supported hypotheses show that several potential factors played a role in influencing students to continuously use the SAM OLE. In contrast, the unsupported hypothesis indicates that the potential factor *Perceived Ease of Use* did not influence the target factor *Continuous Use Intention*. The strength of the relationships between the potential factors (ß) are strong and positive for two of the paths, while the strengths of the relationships of the other paths are weak and mostly positive. Table 6.2 contains the path coefficients and the statistical tests for the relational hypotheses.

Table 6.2 *Path coefficients and statistical tests of relational hypotheses*

Relational hypothesis				Statistics			
Hypo-thesis	Independent factor		Dependent factor	ß Value	t Value	p Value	Status
H_1a	*Information Quality*	►	*Confirmation*	0.599	8.796	< .001	Supported
H_2a	*Confirmation*	►	*Perceived Ease of Use*	0.509	20.135	< .001	Supported
H_4b	*Perceived Usefulness*	►	*Satisfaction*	0.409	2.799	< .001	Supported
H_1c	*Information Quality*	►	*Perceived Usefulness*	0.398	7.813	< .001	Supported
H_6	*Flow*	►	*Continuous Use Intention*[1]	0.344	9.432	< .001	Supported
H_2b	*Confirmation*	►	*Perceived Usefulness*	0.317	12.817	< .001	Supported
H_2c	*Confirmation*	►	*Satisfaction*	0.294	11.332	< .001	Supported

Relational hypothesis				Statistics			
H_4a	*Perceived Usefulness*	►	*Continuous Use Intention*[1]	0.254	5.799	< .001	Supported
H_1b	*Information Quality*	►	*Perceived Ease of Use*	0.249	7.33	< .001	Supported
H_5	*Satisfaction*	►	*Continuous Use Intention*[1]	0.224	1.33	< .001	Supported
H_3c	*Perceived Ease of Use*	►	*Satisfaction*	0.218	4.188	< .001	Supported
H_3b	*Perceived Ease of Use*	►	*Perceived Usefulness*	0.116	5.921	.004	Supported
H_3a	*Perceived Ease of Use*	►	*Continuous Use Intention1*	-0.052	5.079	.192	Not supported

[1] Target factor

6.4 Explanatory power and effect size of structural model

Additional to the determination of the strength and significance of the hypothesised relationships between the potential factors and target factor in the structural model, the model's in-sample explanatory power or predictive power was also determined. The structural model's explanatory power is expressed in terms of the coefficient of determination (R^2), which expresses the proportion of the total variance of a dependent potential factor that is explained by its independent potential factor. The R^2 values for each of the dependent potential factors indicated that a moderate proportion (R^2 between 0.33 and 0.67) of the variance of all the dependent potential factors can be explained by their independent potential factors (Table 6.3) (Chin, 1998). The independent potential factors *Perceived Usefulness*, *Confirmation*, and *Perceived Ease of Use* combined explained 63.6% of the variance in the dependent potential factor *Satisfaction.* Likewise, the three independent potential factors namely *Information Quality, Confirmation* and *Perceived Ease of Use* combined explained 52.4% of the variability of the dependent potential factor *Perceived Usefulness*. Moreover, 47.5% of the proportion of variance of the dependent target factor *Continuous Use Intention,* could be explained by its three independent potential factors namely *Flow, Satisfaction* and *Perceived Usefulness*. A similar proportion of variance (47.2%) when compared to that of *Continuous Use Intention* is explained by the independent potential factors of *Perceived Ease of Use* namely *Information Quality* and *Confirmation.* The proportion of variance (35.9%) explained by the remaining independent potential factor, *Information Quality,* on the dependent potential factor, *Confirmation*, was much lower.

Table 6.3 *R^2 Values for the dependent factors*

Independent factor		Dependent factor	R^2 Original sample mean	R^2 Bootstrap sample mean
Perceived Usefulness *Confirmation* *Perceived Ease of Use*	►	*Satisfaction*	0.636	0.639
Information Quality *Confirmation* *Perceived Ease of Use*	►	*Perceived Usefulness*	0.524	0.528
Flow *Satisfaction* *Perceived Usefulness*	►	*Continuous Intention*[1]	0.475	0.481
Information Quality *Confirmation*	►	*Perceived Ease of Use*	0.472	0.476
Information Quality	►	*Confirmation*	0.359	0.361

[1] Target factor

Once the model's explanatory power had been determined, the size of the effect (f^2) that the independent potential factors had on the dependent potential factors and target factor within the structural model was determined. Based on the f^2 values calculated in this study, the independent potential factor *Information Quality* had a large effect on one of the dependent potential factors, *Confirmation,* with an effect size value greater than 0.35 (Table 6.4) (Hair et al., 2017). In contrast, the independent potential factor *Perceived Ease of Use* had an effect close to zero on the dependent potential factor *Perceived Usefulness.* The three independent potential factors *Confirmation, Perceived Usefulness,* and *Information Quality* moderately impacted the dependent potential factors *Perceived Ease of Use, Satisfaction* and *Perceived Usefulness* ($f^2 \geq 0.15 < 0.35$). The effect sizes of the remaining independent potential factors on the dependent potential factors were relatively small, and ranged from 0.02 to 0.15.

Table 6.4 *Effect size of the independent potential factors on the dependent potential factors*

Structural model relationship			f^2 Original sample	f^2 Bootstrap sample mean
Independent factor		**Dependent factor**		
Information Quality	►	*Confirmation*	0.560	0.570
Confirmation	►	*Perceived Ease of Use*	0.314	0.319
Perceived Usefulness	►	*Satisfaction*	0.263	0.269
Information Quality	►	*Perceived Usefulness*	0.199	0.205
Flow	►	*Continuous Use Intention*[1]	0.119	0.122
Confirmation	►	*Satisfaction*	0.109	0.111
Confirmation	►	*Perceived Usefulness*	0.103	0.105
Information Quality	►	*Perceived Ease of Use*	0.075	0.079
Perceived Ease of Use	►	*Satisfaction*	0.071	0.073
Perceived Usefulness	►	*Continuous Use Intention*[1]	0.054	0.056
Satisfaction	►	*Continuous Use Intention*[1]	0.036	0.039
Perceived Ease of Use	►	*Perceived Usefulness*	0.015	0.017

[1] Target factor

6.5 Predictive accuracy of structural model

In addition to determining the magnitude of the structural model's in-sample predictive power, the model's out-of-sample predictive power or predictive relevance was determined by calculating Stone-Geisser's Q^2 value through the sample reuse technique of blindfolding (Geisser, 1974; Stone, 1974).

Based on the threshold values devised by Geisser (1974) and Stone (1974), the dependent potentiation factors *Confirmation*, *Perceived Ease of Use*, *Perceived Usefulness* and the target factor *Continuous Use Intention,* had a medium out-of-sample predictive power. In contrast, the out-of-sample predictive power of *Satisfaction* was large. Table 6.5 depicts the out-of-sample predictive powers of the reflective dependent potential factors and the target factor of the structural model.

Table 6.5 *Predictive accuracy Q^2 of the dependent factors of the structural model*

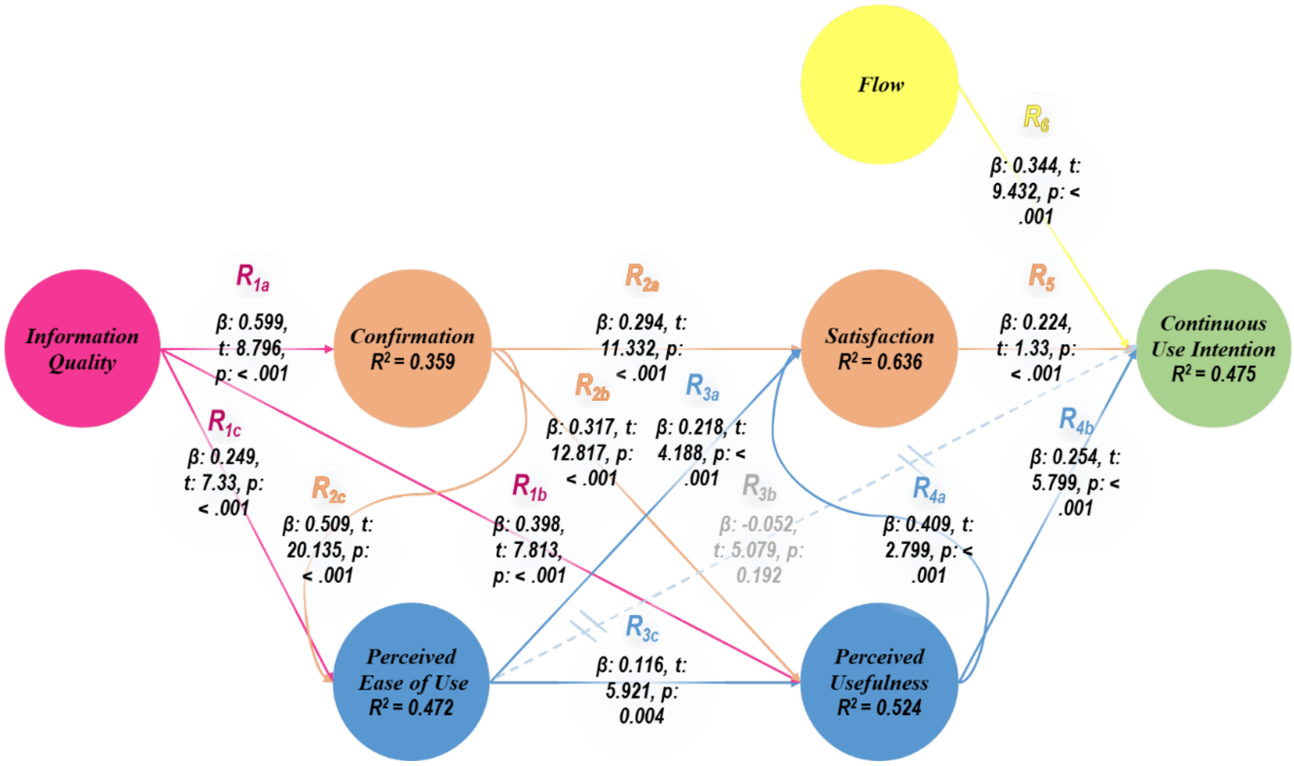
Dependent factor	SSO	SSE	Predictive accuracy Q^2
Confirmation	2379	1850.73	0.222
Continuous Use Intention[1]	2379	1607.47	0.324
Perceived Ease of Use	3172	2305.19	0.273
Perceived Usefulness	3172	2211.81	0.303
Satisfaction	3172	1960.37	0.382

[1] Target factor

6.6 Actual factors identified amongst the potential factors

Based on the assessments of the measurement models and the structural model, the six potential factors were all actual factors, each in their varying relationships, which played a role in influencing students' intention to continuously engage with the SAM OLE. A revised structural model was, thus, constructed, depicting the six actual factors in their relationships with one another and the target factor (Figure 6.2). This revised model depicts the 12 significant path relationships (indicated with R) based on the t-values obtained from testing the relational hypotheses. The hypothesis related to the relationship R_{3b} was non-significant and is indicated with a broken line in the revised model. The revised structural model indicates that the actual factors of *Flow*, *Satisfaction* and *Perceived Usefulness* had a direct influence on the target factor, *Continuous Use Intention.* In addition, the actual factors of *Information Quality*, *Confirmation* and *Perceived Ease of Use* had a direct influence on *Perceived Usefulness*, and the actual factors *Confirmation, Perceived Ease of Use* and *Perceived Usefulness* had a direct influence on *Satisfaction.* It is therefore clear that all the potential factors played a role in their various relationships to one another in the structural model as actual factors that influenced students' intention to continuously engage with the SAM OLE.

Figure 6.2 *Revised structural model depicting the actual factor path relationships that played a role in students' intention to continuously use the SAM OLE*



The 12 significant path relationships of the revised structural model can be described in terms of independent and dependent factor relationships. Table 6.6 provides a description of the different relationships between an independent and its dependent factor, together with the statistical evidence supporting the relationship.

Table 6.6 *Brief descriptions of significant relationships amongst actual factors and target factors*

Significant path relationship	Independent Factor	Dependent factor	Description of relationship	Statistical evidence
R_{1a}	*Information Quality*	*Confirmation*	*Information Quality* had a statistically significant, large and positive effect on *Confirmation*	ß = 0.599 p = < .001 f^2 = 0.560

R_{1b}	*Information Quality*	*Perceived Usefulness*	*Information Quality* had a statistically significant, moderate and positive effect on *Perceived Usefulness*	ß = 0.398 p = < .001 f^2= 0.199
R_{1c}	*Information Quality*	*Perceived Ease of Use*	*Information Quality* had a statistically significant, small and positive effect on *Perceived Ease of Use*	ß = 0.249 p = < .001 f^2= 0.075
R_{2a}	*Confirmation*	*Satisfaction*	*Confirmation* had a statistically significant, small and positive effect on *Satisfaction*	ß = 0.294 p = < .001 f^2= 0.109
R_{2b}	*Confirmation*	*Perceived Usefulness*	*Confirmation* had a statistically significant, small and positive effect on *Perceived Usefulness*	ß = 0.317 p = < .001 f^2= 0.103
R_{2c}	*Confirmation*	*Perceived Ease of Use*	*Confirmation* had a statistically significant, moderate and positive effect on *Perceived Ease of Use*	ß = 0.509 p = < .001 f^2= 0.314
R_{3a}	*Perceived Ease of Use*	*Satisfaction*	*Perceived Ease of Use* had a statistically significant, negligible effect on *Satisfaction*	ß = 0.218 p = < .001 f^2= 0.015
R_{3c}	*Perceived Ease of Use*	*Perceived Usefulness*	*Perceived Ease of Use* had a statistically significant, negligible effect on *Perceived Usefulness*	ß = 0.116 p = 0.004 f^2= 0.003
R_{4a}	*Perceived Usefulness*	*Satisfaction*	*Perceived Usefulness* had a statistically significant, moderate and positive effect on *Satisfaction*	ß = 0.409 p = < .001 f^2= 0.263
R_{4b}	*Perceived Usefulness*	*Continuous Use Intention*[1]	*Perceived Usefulness* had a statistically significant, small and positive effect on Continuous Use Intention	ß = 0.254 p = < .001 f^2= 0.054
R_5	*Satisfaction*	*Continuous Use Intention*[1]	*Satisfaction* had a statistically significant, small and positive effect on *Continuous Use Intention*	ß = 0.224 p = < .001 f^2= 0.036
R_6	*Flow*	*Continuous Use Intention*[1]	*Flow* had a statistically significant, small and positive effect on *Continuous Use Intention*	ß = 0.344 p = < .001 f^2= 0.119

[1] Target factor

6.7 Influence of actual factors on students' continued use of the SAM OLE

After completing the analysis of the structural model and constructing a revised structural model, the influences of the six actual factors on the target factor *Continuous Use Intention* could be described. Four of the actual factors influenced more than one other actual factor in the revised structural model, whereas the actual factors *Flow, Satisfaction* and *Perceived Usefulness* directly influenced the target factor. The influences of the actual factors on the target factor are as follows:

Information Quality

The actual factor *Information Quality* indicates that the quality of information of the SAM OLE had a substantial influence on the confirmation of students' expectations (*Confirmation*) in relation to their use of the SAM OLE. Moreover, this factor also influenced *Perceived Usefulness* and *Perceived Ease of Use* of the SAM OLE as expressed by students, but less so when compared to its influence on *Confirmation*.

Confirmation

The actual factor *Confirmation* indicates that, when students' expectations about their use of the SAM OLE were met, it moderately influenced their perception that the use of the SAM OLE was free of effort (*Perceived Ease of Use)*. Furthermore, this factor also influenced students' *Satisfaction* with the SAM OLE and their *Perceived Usefulness* of the SAM OLE, but less so compared to the influence of *Confirmation* on *Perceived Ease of Use*.

Perceived Ease of Use

The actual factor *Perceived Ease of Use* indicates that the extent to which students perceived the use of the SAM OLE as free of effort had a negligible influence on their perception of *Satisfaction* when using the SAM OLE and its usefulness (*Perceived Usefulness*).

Perceived Usefulness

The actual factor *Perceived Usefulness* indicates that the extent to which the students perceived the SAM OLE to be worthwhile, handy, and beneficial had a moderate influence on their *Satisfaction* with the use of the SAM OLE. In addition, Perceived Usefulness also influenced students' intention to continuously use the SAM OLE *(Continuous Use Intention),* but less so compared to its influence on *Satisfaction*.

Satisfaction

The actual factor *Satisfaction* indicates that the extent to which students were satisfied with the use of the SAM OLE had a small influence on their intention to continuously use the SAM OLE *(Continuous Use Intention).*

Flow

The actual factor *Flow* indicates that the extent to which the students were able to enter a state of flow while using the SAM OLE had a small influence on their intention to continuously use the SAM OLE *(Continuous Use Intention).*

6.8 Summary

The actual factors that influenced first-year students' intention to continuously engage with the SAM OLE in the Basic Digital Literacy module were identified through a rigorous analysis of the data obtained through a questionnaire. The PLS-SEM method was followed to identify the actual factors. After validating the measurement models, the structural model was assessed with several validation measures to identify actual factors amongst the potential factors that influenced students' intention to continuously use the SAM OLE. The validation measures assessed collinearity, significance and relevance, explanatory power, effect size and the predictive accuracy of the model. When the structural model was assessed for collinearity amongst the potential factors and the target factor, it was found to be free of collinearity issues. As no collinearity issues existed amongst the potential factors and the target factor in the structural model, the remaining validation measures were used to assess the structural model. Of the 13 relational hypotheses that were tested, 12 were found to be significant at a 5% significance level. These 12 relationships were then used to construct a revised structural model showing the six actual factors in their relationships with one another and the target factor, *Continuous Use Intention*. The three actual factors that were identified as having an influence on students' intention to continuously engage with the SAM OLE were *Flow*, *Satisfaction* and *Perceived Usefulness*. Furthermore, the three actual factors, *Confirmation*, *Perceived Ease of Use* and *Perceived Usefulness* had a direct influence on *Satisfaction*. Lastly, *Information Quality*, *Confirmation* and *Perceived Ease of Use* directly influenced *Perceived Usefulness* and *Confirmation, Perceived Ease of Use* and *Perceived Usefulness* directly influenced *Satisfaction*.

Chapter 7

Conclusion

7.1 Introduction

In higher education, the teaching and learning landscape is changing rapidly with the ever-increasing development of new digital technologies. These technologies have brought about a range of new possibilities for teaching at universities (Cidral et al., 2018; Willging & Johnson, 2019). Digital learning at universities has become pervasive, particularly in the form of OLEs (Feldman-Maggor et al., 2022). Thus, universities have extensively adopted blended learning in which OLEs are combined with face-to-face learning (Müller & Mildenberger, 2021). These OLEs bring about possibilities to expand the student population beyond the limitations of the physical boundaries of traditional classroom-based learning (Guo et al., 2016; Pudaruth et al., 2010). OLEs create interactive and engaging environments in which students have flexible access to learning materials and are able to study more independently, regardless of time and place (Bayrak & Akcam, 2015). However, the decline in student persistence in engagement with OLEs, and the likelihood of them dropping out of a course, are serious concerns (Meneses & Marlon, 2020; Roca et al., 2006). At the CUT, Free State, some lecturers have integrated OLEs as a component of the student learning experience. In the first year, the SAM OLE was implemented to deliver the basic digital literacy module to all first-year students at the university. This study was therefore undertaken to determine an answer to the overarching research question that underpinned this study, which was to identify which factors influence students' intention to continuously use the OLE for Basic Digital Literacy at the CUT

7.2 Actual factors that influence continuous use intention

In order to have determined an answer to the main research question, answers to three sub-questions had to be obtained. These answers to the sub-questions were obtained as a result of the various objectives completed in each of the three phases of this study. A step-by-step process was followed to identify the actual factors. The first of the sub-research questions answered was:

> Which theories and potential factors can be used to construct a structural model containing potential factors that influence students' intention to continuously use the SAM OLE??

In order to answer the first sub-question, a literature review was conducted to construct a structural model comprising six potential factors along with the target factor, continuous use intention based on a combination of the four theories: ISS (DeLone & McLean, 1992; 2003); the expectation confirmation model (Bhattacherjee, 2001) and its expansion (Thong et al., 2006); and the flow experience model (Csikszentmihalyi, 1990). The constructed structural model showed the relationships between the potential factors and *Continuous Use Intention* (target factor). These relationships represented the 13 relational hypotheses. The second of the sub-research questions answered was:

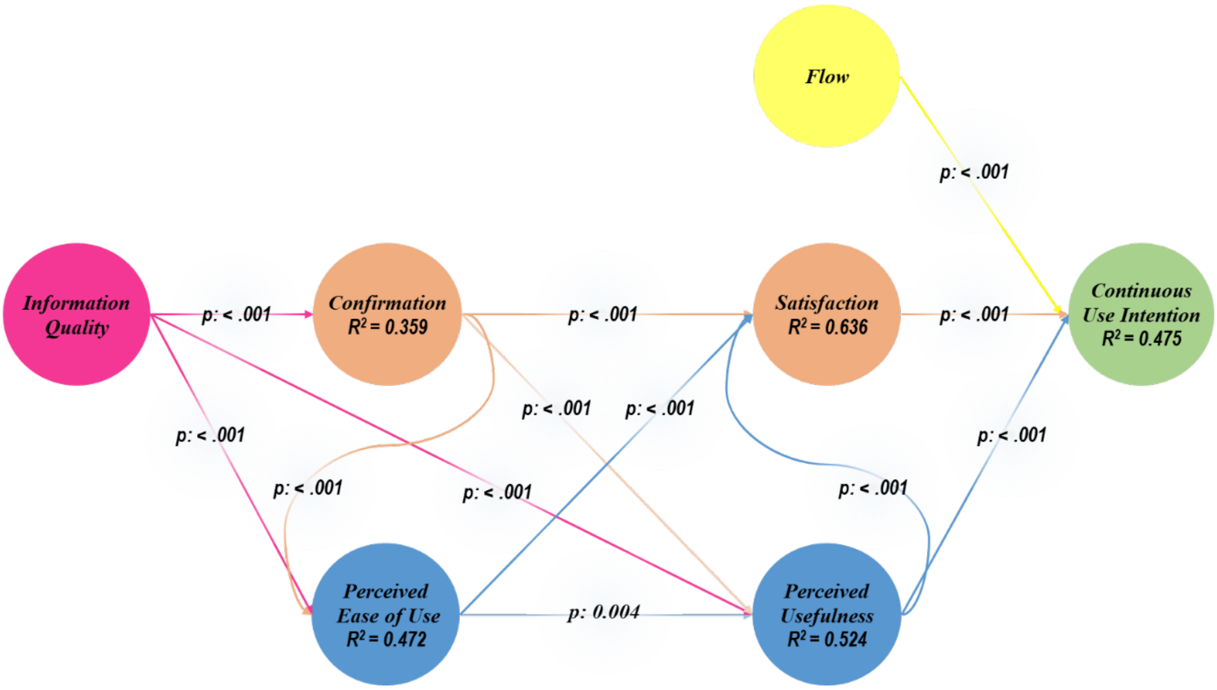
> Which indicators of the measurement models can be used to measure the potential factors that influence students' intention to continuously use the SAM OLE?

In order to answer the second sub-question, the factors (latent variables) were operationalised and validated. Operationalisation was achieved by specifying observable variables (indicators) as items in a questionnaire. This questionnaire, the MIQ, was successfully administered to 793 first-year students. Validation of the MIQ was achieved by testing the MIQ with the data gathered from students. Through testing the student response data with various SEM-PLS techniques using SmartPLS, it was established that the MIQ contains valid and reliable indicators to proceed with the analysis of the structural model. The third of the sub-research questions answered was:

> Which of the potential factors are actual factors that influence a students' intention to continuously use the SAM OLE?

In order to answer the third sub-question, the structural model was validated with the student's response data using a SEM-PLS technique in SmartPLS. The structural model was found to be reliable. Once it was established that the structural model was reliable, hypothesis testing could take place using SmartPLS. Once it was established that the structural model was reliable, hypothesis testing took place using SmartPLS. The 13 relational hypotheses were tested, and 12 were found to be significant at the 5% significance level, and it was revealed that the six tested potential factors were all actual factors. Figure 7.1 Revised structural model depicting the actual factors that influence the target factor *Continuous Use Intention* shows the revised structural model depicting the actual factors that influenced *Continuous Use Intention* in this study. Figure 7.1 shows the revised structural model depicting the actual factors that influenced *Continuous Use Intention* in this study.

Figure 7.1 *Revised structural model depicting the actual factors that influence the target factor Continuous Use Intention*



This study revealed that the actual factor *Flow,* from the flow experience theory (Csikszentmihalyi, 1990), had a direct influence on *Continuous Use Intention*. It could, thus, be concluded from the study that the students were able to become immersed in and maintain a sense of control over their interaction with the SAM OLE and would be able to demonstrate persistent engagement with the OLE. Because *Flow* requires mental involvement by a student, an optimal flow experience could result in a successful learning outcome (Shernoff & Csikszentmihalyi, 2009). Liao (2006) also demonstrated that the flow experience theory works well with an OLE.

This study also revealed that the actual factors *Satisfaction* and *Perceived Usefulness*, which originated from the expectation confirmation model (Bhattacherjee, 2001), also had a direct influence on *Continuous Use Intention*. It could be concluded from the study that the first-year students experienced a sensation of contentment while working with the SAM OLE, which they found useful for achieving their learning goals. Moreover, *Perceived Usefulness* had a significant impact on

Satisfaction, which was also demonstrated by first-year students at the City University of Hong Kong with the Blackboard OLE (Limayem et al., 2003). Therefore, after the initial adoption of an OLE, a state of satisfaction is a requirement for students to continuously engage with an OLE (Cidral et al., 2018; Roca et al., 2006).

This study, furthermore, revealed that the actual factors *Confirmation* and *Perceived Ease of Use* directly influenced other actual factors in the structural model. *Confirmation* from the expectation confirmation model theory (Bhattacherjee, 2001), and *Perceived Ease of Use* from the expanded expectation confirmation model theory (Thong et al., 2006), directly influenced *Satisfaction* and *Perceived Usefulness.* This study, thus, revealed that these students' expectations of the SAM OLE were met and that they perceived their interaction with the OLE to be effort-free. In a study amongst first-year students at the City University of Hong Kong, Limayem et al. (2003) also found that *Confirmation* had a significant effect on *Perceived Usefulness.* In another study amongst first-year students taking an introductory course of management information systems at the university, Limayem and Cheung (2011) showed that *Confirmation* and *Perceived Usefulness* also significantly impacted *Satisfaction.* Conversely, in a study amongst primary school-level e-learning teachers in Indonesia, *Confirmation* did not affect *Perceived Usefulness* (Suzianti & Paramadini, 2021).

Lastly, the study revealed that *Information Quality* from the ISS theory (DeLone & McLean, 1992; 2003) had a direct influence on *Confirmation, Perceived Usefulness* and *Perceived Ease of Use*. It could be concluded that the quality of the information provided by the SAM OLE met these students' expectations. Furthermore, these students also perceived that their interaction with the SAM OLE was useful and free of effort. In a study amongst 313 undergraduate and postgraduate students from eight universities in the Hubei province of China, Zhang et al. (2017) also found that *Information Quality* was an important factor in predicting students' perceptions of how effortless and useful the virtual learning community services were.

7.3 Limitations to the study

This study was subject to certain limitations that dictated the way in which the study was completed. These limitations were related to physical location constraints and sample size implications. In terms of the physical location where the data was collected, the collection process was limited to one campus of one learning institution in a single country at which the researcher is employed on a full-time basis due to time and budget constraints, as well as the logistical practicality of gathering data from a convenience sample. In terms of sample size, not all factors could be included in this study, as including more factors would have implications for sourcing a larger sample size, which would have required more time to complete the study (Deng et al., 2018).

7.4 Significance and prospects

The knowledge gained from this study could shed light on ways to optimise the OLE to improve student engagement and attendance, which, in turn, could enable students to achieve their learning goals. It is expected that revising the delivery platform of the curriculum could lead to overall class performance improvement, which would be advantageous to the institution. Although factors that influence the use of the SAM OLE were identified, the testing of the factors in this study was constrained to a subset of possible theories and factors. Though the population of students were diverse in terms of their study disciplines, efforts in future studies can be made to include students from multiple institutions from different provinces or possibly include international students. Further studies that test different combinations of theories and factors should shed additional light on optimisations of the delivery of basic digital literacy to all first-year students in higher education institutions in general.

7.5 Conclusion

To conclude, in response to a decline observed in student persistence in engagement with an OLE, this multiphase qualitative study was conducted to gain a better understanding of the factors that influence students' intention to continuously use the OLE for Basic Digital Literacy at the CUT. Potential factors were identified from the literature, and though SEM and hypothesis testing data were gathered from 793 first-year students, it was possible to identify that the six potential factors were all actual factors that played a role in students' intention to continuously engage with the SAM OLE for basic digital literacy at the CUT.

References

Abdi, H. (2007). Partial least square regression pls-regression. In N. Salkind (Ed.), *Encyclopedia of measurement and statistics* (pp. 1–13). Sage. http://www.utd.edu/~Herve/Abdi-PLSR2007-pretty.pdf

Abdullah, F., Ward, R., & Ahmed, E. (2016). Investigating the influence of the most commonly used external variables of TAM on students' perceived ease of use (PEOU) and perceived usefulness (PU) of e-portfolios. *Computers in Human Behavior*, *63*, 75–90. https://doi.org/10.1016/j.chb.2016.05.014

Agarwal, R., & Karahanna, E. (2000). Time flies when you're having fun: Cognitive absorption and beliefs about Information Technology usage. *MIS Quarterly*, *24*(4), 665. https://doi.org/10.2307/3250951

Akkoyunlu, B., & Yilmaz-Soylu, M. (2008). Development of a scale on learners' views on blended learning and its implementation process. *Internet and Higher Education*, *11*(1), 26–32. https://doi.org/10.1016/j.iheduc.2007.12.006

Al-Ajam, A. S., & Md Nor, K. (2013). Influencing factors on behavioral intention to adopt Internet banking service. *World Applied Sciences Journal*, *22*(11), 1652–1656.

Alkhaldi, A. N., & Abualkishik, A. M. (2019). The mobile Blackboard system in higher education: Discovering benefits and challenges facing students. *International Journal of Advanced and Applied Sciences*, *6*(6), 6–14. https://doi.org/10.21833/ijaas.2019.06.002

Alsabawy, A. Y., Cater-Steel, A., & Soar, J. (2016). Determinants of perceived usefulness of e-learning systems. *Computers in Human Behavior*, *64*, 843–858.

Ambalov, I. A. (2018). A meta-analysis of IT continuance: An evaluation of the expectation-confirmation model. *Telematics and Informatics*, *35*(6), 1561–1571. https://doi.org/10.1016/j.tele.2018.03.016

Anderson, T. (2009). *The theory and practice of online learning* (2nd ed.). AU Press.

Anthology. (2022). *Blackboard Learn*. https://www.anthology.com/products/teaching-and-learning/learning-effectiveness/blackboard-learn

Aparicio, M., Bacao, F., & Oliveira, T. (2017). Grit in the path to e-learning success. *Computers in Human Behavior*, *66*, 388–399. https://doi.org/10.1016/j.chb.2016.10.009

Asarta, C. J., & Schmidt, J. R. (2020). The effects of online and blended experience on outcomes in a blended learning environment. *Internet and Higher Education*, *44*(June 2018), 100708.

Barnes, S. J., & Böhringer, M. (2011). Modeling use continuance behavior in microblogging services: The case of Twitter. *Journal of Computer Information Systems*, *51*(4), 1–10.

Bayrak, T., & Akcam, B. (2015). Exploring benefits of a web based testing and training tool. *Procedia – Social and Behavioral Sciences*, *195*, 1032–1041. https://doi.org/10.1016/j.sbspro.2015.06.146

Bernard, R. M., Abrami, P. C., Borokhovski, E., Wade, C. A., Tamim, R. M., Surkes, M. A., & Bethel, E. C. (2009). A meta-analysis of three types of interaction treatments in distance education. *Review of Educational Research*, *79*(3), 1243–1289.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, *25*(3), 351–370.

Bollen, K. A., & Bauldry, S. (2011). Three Cs in measurement models: Causal indicators, composite indicators, and covariates. *Psychological Methods*, *16*(3), 265–284.

Broadband Commission for Sustainable Development. (2017). *Working group on education: Digital skills for life and work*.

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. Internet and Higher Education. *Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Brown, M., Mccormack, M., Reeves, J., Brooks, D. C., Grajek, S., Bali, M., Bulger, S., Dark, S., Engelbert, N., Gannon, K., Gauthier, A., Gibson, D., Gibson, R., Lundin, B., Veletsianos, G., & Weber, N. (2020). *2020 EDUCAUSE Horizon Report*. Teaching and Learning Edition. Educause.

Burger, B. (2019, January 16). *Is digital intelligence the key to globalization 4.0?* World Economic Forum. https://www.weforum.org/agenda/2019/01/is-digital-intelligence-the-key-to-globalization-4-0/

Bygstad, B., Øvrelid, E., Ludvigsen, S., & Dæhlen, M. (2022). From dual digitalization to digital learning space: Exploring the digital transformation of higher education. *Computers and Education*, *182*(August 2021).

Caffaro, F., Micheletti Cremasco, M., Roccato, M., & Cavallo, E. (2020). Drivers of farmers' intention to adopt technological innovations in Italy: The role of information sources, perceived usefulness, and perceived ease of use. *Journal of Rural Studies*, *76*(March), 264–271. https://doi.org/10.1016/j.jrurstud.2020.04.028

Cengage. (2022). *SAM premier training for Microsoft Office*. https://www.cengage.co.uk/sam/

Cengage Learning. (2017). *Research insights: Three key components to empowering student success with Microsoft Office skills and on the MOS exams*.

Center for Reimagining Learning. (2022). *Open edX - Deliver inspiring learning experiences on any scale*. https://openedx.org/

Ceresia, F. (2016). Interactive learning environments (ILEs) as effective tools for teaching social sciences. *Procedia - Social and Behavioral Sciences*, *217*, 512–521.

Chang, C., Hajiyev, J., & Su, C.-R. (2017). Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Computers & Education*, *111*, 128–143. https://doi.org/10.1016/j.compedu.2017.04.010

Chang, Y. P., & Zhu, D. H. (2012). The role of perceived social capital and flow experience in building users' continuance intention to social networking sites in China. *Computers in Human Behavior*, *28*(3), 995–1001.

Chen, H. J. (2010). Linking employees' e-learning system use to their overall job outcomes: An empirical study based on the IS success model. *Computers and Education*, *55*(4), 1628–1639. https://doi.org/10.1016/j.compedu.2010.07.005

Chen, J., Wang, M., Kirschner, P. A., & Tsai, C. C. (2018). The role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A meta-analysis. *Review of Educational Research*, *88*(6), 799–843.

Chi, T. (2018). Understanding Chinese consumer adoption of apparel mobile commerce: An extended TAM approach. *Journal of Retailing and Consumer Services*, *44*(July), 274–284.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii–xvi.

Chiu, C. M., Hsu, M.-H., Sun, S. Y., Lin, T. C., & Sun, P. C. (2005). Usability, quality, value and e-learning continuance decisions. *Computers and Education*, *45*(4), 399–416.

Cho, H., Chi, C., & Chiu, W. (2020). Understanding sustained usage of health and fitness apps: Incorporating the technology acceptance model with the investment model. *Technology in Society*, *63*(October), 101429. https://doi.org/10.1016/j.techsoc.2020.101429

Cho, Y. H., Choi, H., Shin, J., Yu, H. C., Kim, Y. K., & Kim, J. Y. (2015). Review of research on online learning environments in higher education. *Procedia – Social and Behavioral Sciences*, *191*, 2012–2017. https://doi.org/10.1016/j.sbspro.2015.04.634

Choi, D., & Kim, J. (2004). Why people continue to play online games: In search of critical design factors to increase customer loyalty to online contents. *Cyberpsychology and Behavior*, *7*(1), 11–24.

Choudhury, H., & Khataniar, G. (2018). Structural equation modeling for investigating the factors affecting the faculty members adoption and use of e-learning platform in academic purposes: An empirical validation in higher educational context. *Asian Journal of Computer Science and Technology*, *7*(2), 21–29.

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, *65*, 276–284. https://doi.org/10.1016/j.chb.2016.07.047

Cidral, W. A., Oliveira, T., di Felice, M., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers & Education*, *122*(February), 273–290. https://doi.org/10.1016/j.compedu.2017.12.001

Civelek, M. E. (2018). *Essentials of structural equation modeling*. Zea Books.

Codecademy. (2022). *Learn to code - for free. Codecademy*. http://www.codecademy.com/

Cornerstone. (2022). *Learning experience platform. LXP – EdCast*. https://www.edcast.com/

Coursera. (2022). *Degrees, certificates, & free online courses*. https://www.coursera.org/

Craig, R. (2019, March). *America's skills gap: Why it's real, and why it matters*. Progressive Policy Institute. https://www.progressivepolicy.org/wp-content/uploads/2019/03/SkillsGapFinal.pdf

Crawford, J., Butler-Henderson, K., Rudolf, J., Malkawi, B. Glowatz, M., Burton, R.O, Magni, P. A. (2020). COVID-19: 20 countries' higher education intra-period digital pedagogy responses. *Journal of Applied Learning & Teaching*, *3*(1). https://doi.org/10.37074/jalt.2020.3.1.7

Crotty, M. (1998). *The foundations of social research* (1st ed.). Sage.

Csikszentmihalyi, M. (1990). *Flow: The psychology of optimal experience.* Vol. 16, Issue 3). Harper Perennial.

D2L. (2022). *D2L Middle East & Africa. Brightspace* |. https://www.d2l.com/en-mea/brightspace/

Dai, H. M., Teo, T., Rappa, N. A., & Huang, F. (2020). Explaining Chinese university students' continuance learning intention in the MOOC setting: A modified expectation confirmation model perspective. *Computers and Education*, *150*(February), 103850.

Dalton, W., & Turner, B. (2021). *Best online learning platforms of 2021: LMS and VLE for education*. Techradar.com. https://www.techradar.com/uk/best/best-online-learning-platforms

Daɫhan, G., & Akkoyunlu, B. (2016). Modeling the continuance usage intention of online learning environments. *Computers in Human Behavior*, *60*, 198–211. https://doi.org/10.1016/j.chb.2016.02.066

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339.

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International Journal of Man-Machine Studies*, *38*(3), 475–487.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60–95.

DeLone, W. H., & Mclean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Deng, L., Yang, M., & Marcoulides, K. M. (2018). Structural equation modeling with many variables: A systematic review of issues and developments. *Frontiers in Psychology*, *9*(April). https://doi.org/10.3389/fpsyg.2018.00580

Docebo. (2021). *Docebo Learning Suite: Learn. Develop. Succeed.* https://www.docebo.com/

Ellis, R. A., & Goodyear, P. (2016). Models of learning space: integrating research on space, place and learning in higher education. *Review of Education*, *4*(2), 149–191.

Eon Reality. (2022). *EON-XR platform*. https://eonreality.com/platform/

Feldman-Maggor, Y., Blonder, R., & Tuvi-Arad, I. (2022). Let them choose: Optional assignments and online learning patterns as predictors of success in online general chemistry courses. *The Internet and Higher Education*, *55*(May), 100867. https://doi.org/10.1016/j.iheduc.2022.100867

Finstad, K. (2010). Response interpolation and scale sensitivity: evidence against 5-point scales. *Journal of User Experience, 5*(3), 104–110.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.1177/002224378101800313

Gallardo-Echenique, E. E., Minelli de Oliveira, J., Marqués-Molias, L., & Esteve-Mon, F. (2015). Digital competence in the knowledge society. *MERLOT Journal of Online Learning and Teaching*, *11*(1), 1–16.

Garrison, D. R., & Vaughan, N. D. (2012). *Blended learning in higher education: Framework, principles, and guidelines*. John Wiley & Sons.

Gefen, D., Rigdon, E. E., & Straub, D. (2011). Editor's comments: An update and extension to SEM guidelines for administrative and social science research. *MIS Quarterly*, *35*(2), iii–xiv.

Gefen, & Straub. (2003). Managing user trust in B2C e-Services. *E-Service Journal*, *2*(2), 7. https://doi.org/10.2979/esj.2003.2.2.7

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, *61*(1), 101–107. https://doi.org/10.1093/biomet/61.1.101

Gibbs, S., Steel, G., & McKinnon, A. (2014). *Are workplace end-user computing skills at a desirable level? A New Zealand perspective.* 20th Americas Conference on Information Systems, AMCIS 2014.

Goodwin, J., Kilty, C., Kelly, P., O'Donovan, A., White, S., & O'Malley, M. (2022). Undergraduate student nurses' views of online learning. *Teaching and Learning in Nursing* (in press). https://doi.org/10.1016/j.teln.2022.02.005

Guo, Z., Xiao, L., van Toorn, C., Lai, Y., & Seo, C. (2016). Promoting online learners' continuance intention: An integrated flow framework. *Information and Management*, *53*(2), 279–295.

Hair, J. F., Black, B. J., Babin, R. E., Anderson, R. L., & Tatham. (2006). *Multivariate data analysis* (6th ed.). Pearson.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage.

Hair, J. F., Hult, G. T. M., Ringle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer.

Harvard Business School. (2022). *Harvard Business School Online*. https://online.hbs.edu/

Henderson, R., & Divett, M. J. (2003). Perceived usefulness, ease of use and electronic supermarket use. *International Journal of Human Computer Studies*, *59*(3), 383–395. https://doi.org/10.1016/S1071-5819(03)00079-X

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Hernández-García, Á., González-González, I., Jiménez-Zarco, A. I., & Chaparro-Peláez, J. (2015). Applying social learning analytics to message boards in online distance learning: A case study. *Computers in Human Behavior*, *47*, 68–80.

Herrington, A., & Herrington, J. (2007). What is an authentic learning environment? In A. Herrington, & J. Herrington (Eds.), *Authentic learning environments in higher education*. IGI Global. https://ro.uow.edu.au/edupapers/897

Hilliard, L. P., & Stewart, M. K. (2019). Time well spent: Creating a community of inquiry in blended first-year writing courses. *Internet and Higher Education*, *41*, 11–24.

Holmberg, B. (2005). *The evolution, principles and practices of distance education*. Studien und Berichte der Arbeitsstelle Fernstudienforschung der Carl von Ossietzky Universität Oldenburg. Vol. 11. BIS-Verlag der Carl von Ossietzky Universität Oldenburg.

Hudson, E., Clavel, N., Kilpatrick, K., & Lavoie-Tremblay, M. (2021). Effective online learning strategies for leadership and policy undergraduate courses for nursing students: a rapid review. *Journal of Professional Nursing*, *37*(6), 1079–1085.

IBM. (2022). *SPSS Statistics*. https://www.ibm.com/products/spss-statistics

Instructure. (2022). *Higher education LMS features. Canvas learning management system*. https://www.instructure.com/higher-education/products/canvas/canvas-lms

Iivari, J. (2015). Making sense of the history of information systems research 1975-1999: A view of highly cited papers. *Communications of the Association for Information Systems*, *36*(1), 515–561. https://doi.org/10.17705/1CAIS.03625

Jang, M., Aavakare, M., Nikou, S., & Kim, S. (2021). The impact of literacy on intention to use digital technology for learning: A comparative study of Korea and Finland. *Telecommunications Policy*, *45*(7). https://doi.org/10.1016/j.telpol.2021.102154

Ji, H., Park, S., & Shin, H. W. (2022). Investigating the link between engagement, readiness, and satisfaction in a synchronous online second language learning environment. *System*, *105*(December 2021), 102720.

Johnson, L., Adams Becker, S., and Hall, C. (2015). *NMC technology outlook for Scandinavian schools: A Horizon Project regional report*. New Media Consortium.

Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V., & Hatala, M. (2015). Learning at distance: Effects of interaction traces on academic achievement. *Computers and Education*, *87*, 204–217.

Keith, T. Z. (2019). *Multiple regression and beyond* (3rd ed.). Taylor & Francis.

Khan Academy. (2019). *Free online courses, lessons and practice*. https://www.khanacademy.org/

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information and Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers and Education*, *104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Kohnke, L., & Moorhouse, B. L. (2022). Facilitating synchronous online language learning through Zoom. *RELC Journal*, *53*(1), 296–301. https://doi.org/10.1177/0033688220937235

Koorsse, M., Calitz, A. P., & Zietsman, J. (2016). Criteria for evaluating automated grading systems to assess Microsoft Office skills. In S. Gunter (Ed.), *Annual Conference of the Southern African Computer Lecturers' Association* (Vol. 642, pp. 51–58). Springer International Publishing AG. https://doi.org/10.1007/978-3-319-47680-3_5

Kumar, A., Kumar, P., Palvia, S. C. J., & Verma, S. (2017). Online education worldwide: Current status and emerging trends. *Journal of Information Technology Case and Application Research*, *19*(1), 3–9.

Kumari, T.A., Hemalatha, C. H., Subhani Ali, M., & Naresh, R. (2020). Survey on impact and learning's of the online courses on the present era. *Procedia Computer Science*, *172*, 82–91. https://doi.org/10.1016/j.procs.2020.05.167

Larsen, T. J., Sørebø, A. M., & Sørebø, Ø. (2009). The role of task-technology fit as users' motivation to continue information system use. *Computers in Human Behavior*, *25*(3), 778–784.

Lee, M. (2010). Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation-confirmation model. *Computers and Education*, *54*(2), 506–516.

Lee, M., & Tsai, T. (2010). What drives people to continue to play online games? An extension of technology model and theory of planned behavior. *International Journal of Human-Computer Interaction*, *26*(6), 601–620.

Li, C., & Lalani, F. (2020). *The COVID-19 pandemic has changed education forever. This is how*. World Economic Forum. https://www.polyu.edu.hk/sllo/hackathon/index.php/library/50-the-covid-19-pandemic-has-changed-education-forever-this-is-how

Li, M., Oh, L. bin, & Wang, K. (2009). A process virtualization theory approach to understanding the usage continuance of cross-channel instant messaging. *Proceedings of the International Conference on Electronic Business (ICEB)*, *January*, 739–745.

Liao, C., Chen, J.-L., & Yen, D. C. (2007). Theory of planning behavior (TPB) and customer satisfaction in the continued use of e-service: An integrated model. *Computers in Human Behavior*, *23*(6), 2804–2822.

Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology adoption behavior life cycle: Toward a technology continuance theory (TCT). *International Journal of Information Management*, *29*(4), 309–320.

Liao, L. (2006). A flow theory perspective on learner motivation and behavior in distance education. *Distance Education*, *27*(1), 45–62. https://doi.org/10.1080/01587910600653215

Limayem, M., Cheung, C., & Chan, G. (2003). *Explaining information systems adoption and post-adoption: Toward an integrative model.* ICIS 2003 Proceedings. http://aisel.aisnet.org/icis2003/59

Limayem, M., & Cheung, C. M. K. (2008). Understanding information systems continuance: The case of Internet-based learning technologies. *Information and Management*, *45*(4), 227–232.

Limayem, M., & Cheung, C. M. K. (2011). Predicting the continued use of Internet-based learning technologies: the role of habit. *Behaviour & Information Technology*, *30*(1), 91–99. https://doi.org/10.1080/0144929X.2010.490956

Lin, M. H., Chen, H. C., & Liu, K. S. (2017). A study of the effects of digital learning on learning motivation and learning outcome. *Eurasia Journal of Mathematics, Science and Technology Education*, *13*(7), 3553–3564. https://doi.org/10.12973/eurasia.2017.00744a

Lin, W. S., & Wang, C. H. (2012). Antecedences to continued intentions of adopting e-learning system in blended learning instruction: A contingency framework based on models of information system success and task-technology fit. *Computers and Education*, *58*(1), 88–99.

Lu, Y., Zhou, T., & Wang, B. (2009). Exploring Chinese users' acceptance of instant messaging using the theory of planned behavior, the technology acceptance model, and the flow theory. *Computers in Human Behavior*, *25*(1), 29–39. https://doi.org/10.1016/j.chb.2008.06.002

Mahfuz, I., & Saha, S. P. (2015). Adoption of mobile money transfer services in Bangladesh: A structural equation modeling approach. *Journal of Marketing and Consumer Research*, *15*(15), 5–16.

Malaquias, R. F., & Silva, A. F. (2020). Understanding the use of mobile banking in rural areas of Brazil. *Technology in Society*, *62*(April), 101260.

Matthews, K., Janicki, T., He, L., & Patterson, L. (2012). Implementation of an automated grading system with an adaptive learning component to affect student feedback and response time. *Journal of Information Systems Education*, *23*(1), 71–83.

McGraw Hill Higher Education. (2022). *SIMnet keep IT simple!* https://www.mheducation.com/highered/simnet.html

Meneses, J., & Marlon, X. (2020). *Dropout in online higher education. A scoping review from 2014 to 2018.* Universitat Oberta de Catalunya. https://doi.org/10.7238/uoc.dropout.factors.2020

Microsoft. (2022). *Employee experience and engagement. Microsoft Viva*. https://www.microsoft.com/en-za/microsoft-viva

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, *45*, 359–374.

Monecke, A., & Leisch, F. (2012). SemPLS: Structural equation modeling using partial least squares. *Journal of Statistical Software*, *48*.

Moodle. (2022). *LMS platform – Moodle LMS – learning management system*. https://moodle.com/solutions/lms/

Moon, J., & Kim, Y. (2001). Extending the TAM for a World-Wide-Web context. *Information and Management*, *38*(4), 217–230.

Moore, J. L., Dickson-Deane, C., & Galyen, K. (2011). E-Learning, online learning, and distance learning environments: Are they the same? *Internet and Higher Education*, *14*(2), 129–135.

Müller, C., & Mildenberger, T. (2021). Facilitating flexible learning by replacing classroom time with an online learning environment: A systematic review of blended learning in higher education. *Educational Research Review*, *34*(April), 100394. https://doi.org/10.1016/j.edurev.2021.100394

Myklebust, J. P., & Smidt, H. (2021, January 29). What is the role of universities in global upskilling? *University World News*. https://www.universityworldnews.com/post.php?story=20210129110449887

Mystakidis, S., Fragkaki, M., & Filippousis, G. (2021). Ready teacher one: Virtual and augmented reality online professional development for K-12 school teachers. *Computers*, *10*(10), 1–16. https://doi.org/10.3390/computers10100134

Nagel, D. (2011, July 13). *Blackboard partners with major education publishers for LMS integration*. Campus Technology. https://campustechnology.com/articles/2011/07/13/blackboard-partners-with-major-education-publishers-for-lms-integration.aspx

Nastjuk, I., Herrenkind, B., Marrone, M., Brendel, A. B., & Kolbe, L. M. (2020). What drives the acceptance of autonomous driving? An investigation of acceptance factors from an end-user's perspective. *Technological Forecasting and Social Change*, *161*, 120319. https://doi.org/10.1016/J.TECHFORE.2020.120319

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, *17*(4), 460. https://doi.org/10.2307/3150499

Oncu, S., & Cakir, H. (2011). Research in online learning environments: Priorities and methodologies. *Computers and Education*, *57*(1), 1098–1108. https://doi.org/10.1016/j.compedu.2010.12.009

Central University of Technology, Free State

Owston, R., & York, D. N. (2018). The nagging question when designing blended courses: Does the proportion of time devoted to online activities matter? *Internet and Higher Education*, *36*, 22–32.

Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018). Online learning: Adoption, continuance, and learning outcome - A review of literature. *International Journal of Information Management*, *43*, 1–14.

Pearson. (2022). *MyLab IT*. https://mlm.pearson.com/northamerica/myitlab/

Piccoli, G., Ahmad, R., & Ives, B. (2001). Web-based virtual learning environments: A research framework and a preliminary assessment of effectiveness in basic IT skills training. *MIS Quarterly: Management Information Systems*, *25*(4), 401–426.

Popovici, A., & Mironov, C. (2015). Students' perception on using eLearning technologies. *Procedia – Social and Behavioral Sciences*, *180*, 1514–1519. https://doi.org/10.1016/j.sbspro.2015.02.300

Pudaruth, S., Moloo, R. K., Mantaye, A., & Bibi, J. N. (2010). A survey of e-learning platforms in Mauritius. *WCE 2010 - World Congress on Engineering 2010*, *1*, 415–420.

QuestionPro. (2022). *QuestionPro survey software*. https://www.questionpro.com/survey-software/

Rai, A., Lang, S. S., & Welker, R. B. (2002). Assessing the validity of IS success models: An empirical test and theoretical analysis. *Information Systems Research*, *13*(1), 50–69. https://doi.org/10.1287/isre.13.1.50.96

Ramayah, T., Ahmad, N. H., & Lo, M. C. (2010). The role of quality factors in intention to continue using an e-learning system in Malaysia. *Procedia – Social and Behavioral Sciences*, *2*(2), 5422–5426. https://doi.org/10.1016/j.sbspro.2010.03.885

Raykov, T., & Marcoulides, G. A. (2006). *A first course in structural equation modeling* (2nd ed.). Lawrence Erlbaum Associates.

Renny, Guritno, S., & Siringoringo, H. (2013). Perceived usefulness, ease of use, and attitude towards online shopping usefulness towards online airlines ticket purchase. *Procedia – Social and Behavioral Sciences*, *81*, 212–216. https://doi.org/10.1016/j.sbspro.2013.06.415

Reuning, K., & Plutzer, E. (2020). Valid vs. invalid straightlining: The complex relationship between straightlining and data quality. *Survey Research Methods*, *14*(5), 439–459. https://doi.org/10.18148/srm/2020.v14i5.7641

Ringle, C. M., Wende, S., & Becker, J. M. (2015). *SmartPLS* (No. 3). SmartPLS GmbH. http://www.smartpls.com

Roca, J. C., Chiu, C.-M., & Martínez, F. J. (2006). Understanding e-learning continuance intention: An extension of the technology acceptance model. *International Journal of Human-Computer Studies*, *64*(8), 683–696. https://doi.org/10.1016/j.ijhcs.2006.01.003

Rockart, J. F. (1982). Changing role of the information systems executive: A critical success factors perspective. In *Proceedings of the International Conference on Information Systems*.

Rodríguez-Ardura, I., & Meseguer-Artola, A. (2016). What leads people to keep on e-learning? An empirical analysis of users' experiences and their effects on continuance intention. *Interactive Learning Environments*, *24*(6), 1030–1053. https://doi.org/10.1080/10494820.2014.926275

Ryan, J. (2010). *A history of the internet and the digital future*. Reaktion Books. http://curtin.eblib.com.au/patron/FullRecord.aspx?p=618772

Sakai. (2022). *Sakai learning management system*. https://www.sakailms.org/

SAP Litmos. (2022). *SAP Litmos: Corporate training solutions*. https://www.litmos.com/

Saqr, M., & López-Pernas, S. (2021). The longitudinal trajectories of online engagement over a full program. *Computers and Education*, *175*. https://doi.org/10.1016/j.compedu.2021.104325

Sam, C., & Van der Sijde, P. (2014). Understanding the concept of the entrepreneurial university from the perspective of higher education models. *Higher Education*, *68*(6), 891–908. https://doi.org/10.1007/s10734-014-9750-0

Saunders, M., Lewis, P., & Thornhill, A. (2007). Principles and practices of structural equation modelling. In T. D. Little (Ed.), *Methodology in the social sciences* (4th ed.). The Guilford Press.

Saunders, M. N. K., Lewis, P., Thornhill, A., & Bristow, A. (2019). Understanding research philosophy and approaches to theory development. In M. N. K. Saunders, P. Lewis, & Thornhill, A. (Eds.), *Research methods for business students* (8th ed., pp. 122–161). Pearson Education.

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2009). *Custom LMS: Key features, benefits, development costs*. Pearson Education.

Schmidt, J. A. (2010). Flow in education. In B. McGaw, & E.L. Baker (Eds.), *International encyclopedia of education* (pp. 605–611). Elsevier Science.

Schmidt, J. A., Shernoff, D. J., & Csikszentmihalyi, M. (2014). Individual and situational factors related to the experience of flow in adolescence a multilevel approach. In M. Csikszentmihalyi, *Applications of flow in human development and education: The collected works of Mihaly Csikszentmihalyi* (pp. 379–405). Springer. https://doi.org/10.1007/978-94-017-9094-9_20

Schwab, K. (2016). *The Fourth Industrial Revolution: what it means and how to respond*. Foreign Affairs.

ScienceSoft. (2022). *Custom LMS: Key features, benefits, development costs*. https://www.scnsoft.com/elearning/lms/custom

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information Systems Research*, *8*(3), 240–253. https://doi.org/10.1287/isre.8.3.240

Segars, A. H., & Grover, V. (1993). Re-examining perceived ease of use and usefulness: A confirmatory factor analysis. *MIS Quarterly: Management Information Systems*, *17*(4), 517–525. https://doi.org/10.2307/249590

Shernoff, D. J., & Csikszentmihalyi, M. (2009). Flow in schools: Cultivating engaged learners and optimal learning environments. In Allen, K.-A., Furlong, M.J., Vella-Brodrick, D., & Suldo, S.M. (Eds.), *Handbook of positive psychology in schools* (pp. 131–145). https://doi.org/10.4324/9780203884089-20

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, *69*(10), 4552–4564.

Siemens, G., Gašević, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended, and online learning*. Atabasca University Press.

Spector, J. M., Merrill, M. D., Elen, J., & Bishop, M. J. (Eds.) (2014). *Handbook of research on educational communications and technology* (4th ed.). Springer.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society. Series B (Methodological)*, *36*(2), 111–147.

Su, W., Luo, D., Zhang, C., & Zeng, S. (2022). Evaluation of online learning platforms based on probabilistic linguistic term sets with self-confidence multiple attribute group decision making method. *Expert Systems with Applications*, *208*(July), 118153.

Sun, Q., Wang, C., & Cao, H. (2009). An extended TAM for analyzing adoption behavior of mobile commerce. *2009 Eighth International Conference on Mobile Business*, 52–56. https://doi.org/10.1109/ICMB.2009.16

Sun, Y., Zhao, Q., Li, X., & Sun, H. (2021). Online learning status of nursing undergraduates during the special period of “class suspension with learning uninterrupted.” *Chinese Journal of Nursing*, *18*(6), 515–519.

Suzianti, A., & Paramadini, S. A. (2021). Continuance intention of e-learning: The condition and its connection with open innovation. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 97. https://doi.org/10.3390/JOITMC7010097

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. *Procedia Manufacturing*, *22*, 960–967. https://doi.org/10.1016/j.promfg.2018.03.137

Tamm, S. (2021). *All 10 types of e-learning explained*. E-Student.Org. https://e-student.org/types-of-e-learning/

Tang, C. M., & Chaw, L. Y. (2015). Digital literacy: A prerequisite for effective learning in a blended learning environment? *Proceedings of the European Conference on E-Learning (ECE)L*, *14*(1), 54–65.

Taylor, S., & Todd, P. (1995). Decomposition and crossover effects in the theory of planned behavior: A study of consumer adoption intentions. *International Journal of Research in Marketing*, *12*(2), 137–155.

Terzis, V., Moridis, C. N., & Economides, A. A. (2013). Continuance acceptance of computer based assessment through the integration of user's expectations and perceptions. *Computers and Education*, *62*, 50–61. https://doi.org/10.1016/j.compedu.2012.10.018

Thong, J. Y. L., Hong, S. J., & Tam, K. Y. (2006). The effects of post-adoption beliefs on the expectation-confirmation model for information technology continuance. *International Journal of Human Computer Studies*, *64*(9), 799–810. https://doi.org/10.1016/j.ijhcs.2006.05.001

Turk, M., Heddy, B. C., & Danielson, R. W. (2022). Teaching and social presences supporting basic needs satisfaction in online learning environments: How can presences and basic needs happily meet online? *Computers and Education*, *180*(May 2021), 104432.

Turner, B., & DeMuro, J. P. (2022, July 27). *Best online learning platforms of 2022*. Techradar.pro. https://www.techradar.com/best/best-online-learning-platforms

Udacity. (2022). *Learn the latest tech skills; advance your career.* https://www.udacity.com/

Udeogalanya, V. (2022). Aligning digital literacy and student academic success: Lessons learned from COVID-19 pandemic. *International Journal of Higher Education Management*, *8*(2), 10–12. https://doi.org/10.24052/ijhem/v08n02/art-4

Unimersiv. (2019). *VR rraining // Virtual reality education - Unimersiv*. https://unimersiv.com/

University of Notre Dame. (2022). *Data science.* https://datascience.nd.edu/

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365.

Venter, M., & Swart, A. J. (2018). An integrated model for the continuous use intention of Microsoft Office simulation software. *IEEE Global Engineering Education Conference (EDUCON), April 2018*, 320–329. https://doi.org/10.1109/EDUCON.2018.8363246

Wang, L. Y. K., Lew, S. L., Lau, S. H., & Leow, M. C. (2019). Usability factors predicting continuance of intention to use cloud e-learning application. *Heliyon*, *5*(6), e01788. https://doi.org/10.1016/j.heliyon.2019.e01788

Wang, Q., Quek, C. L., & Hu, X. (2017). Designing and improving a blended synchronous learning environment: An educational design research. *International Review of Research in Open and Distance Learning*, *18*(3), 99–118.

Wang, Y., Lin, H., & Luarn, P. (2006). Predicting consumer intention to use mobile service. *Information Systems Journal*, *16*(2), 157–179.

Whitemore, B. (2018). *6 types of online learning platforms*. Extension Engine Blog. https://blog.extensionengine.com/six-types-of-online-learning-platforms

Wiley & Sons. (2022). *WileyPLUS - WileyPLUS*. https://www.wileyplus.com/

Willging, P. A., & Johnson, S. D. (2019). Factors that influence students' decision to dropout of online courses. *Online Learning*, *13*(3), 115–127. https://doi.org/10.24059/olj.v13i3.1659

World Economic Forum. (2020, October). *The future of jobs report 2020*. No. 1163. https://www.weforum.org/reports/the-future-of-jobs-report-2020/digest

Xiao, J., & Goulias, K. G. (2022). Perceived usefulness and intentions to adopt autonomous vehicles. *Transportation Research Part A: Policy and Practice*, *161*, 170–185. https://doi.org/10.1016/j.tra.2022.05.007

Yan, M., Filieri, R., & Gorton, M. (2021). Continuance intention of online technologies: A systematic literature review. *International Journal of Information Management*, *58*, 1–13. https://doi.org/10.1016/j.ijinfomgt.2021.102315

You, J. W., & Kang, M. (2014). The role of academic emotions in the relationship between perceived academic control and self-regulated learning in online learning. *Computers and Education*, *77*, 125–133. https://doi.org/10.1016/j.compedu.2014.04.018

Zhang, M., Liu, Y., Yan, W., & Zhang, Y. (2017). Users' continuance intention of virtual learning community services: the moderating role of usage experience. *Interactive Learning Environments*, *25*(6), 685–703. https://doi.org/10.1080/10494820.2016.1172242

Zhang, S., Ma, R., Wang, Z., Li, G., & Fa, T. (2022). Academic self-concept mediates the effect of online learning engagement on deep learning in online courses for Chinese nursing students: A cross-sectional study. *Nurse Education Today*, *117*(October). https://doi.org/10.1016/j.nedt.2022.105481

Zhang, Y., Zhao, G., & Zhou, B. (2021). Does learning longer improve student achievement? Evidence from online education of graduating students in a high school during COVID-19 period. *China Economic Review*, *70*(September).

Zhou, T., & Lu, Y. (2011). Examining mobile instant messaging user loyalty from the perspectives of network externalities and flow experience. *Computers in Human Behavior*, *27*(2), 883–889.

Appendix A: Ethical Considerations

FACULTY RESEARCH AND INNOVATION COMMITTEE

RESEARCH ETHICS APPROVAL LETTER

Date: 28 May 2018

This is to confirm that:

Applicant's Name	Ms A Nortje
Supervisor Name for Student Project (where applicable)	Mrs M Venter
Level of Qualification for Student Project (where applicable)	Masters Study
Tittle of research project	Questionnaire approval for SAM research project

Ethical clearance has been provided by the Faculty Research and Innovation Committee on 24 May 2018 in view of the CUT Research Ethics and Integrity Framework, 2016 with reference number FEIT 5/18 - 6:29/24-5-18.

The following special conditions were set:

- [X] None
- [ ] Specific conditions

We wish you success with your research project.

Vermaak

Prof HJ Vermaak
(FRIC Chairperson)

Central University of Technology, Free State

Appendix B: Consent Form

Consent Form

Consent to participate in a questionnaire for the following research topic:

Exploring factors influencing the Continuance Use Intention (CUI) of Interactive Online Learning Environments (IOLEs) for the Central University of Technology

The aim of this study is to identify factors that would be able to predict the CUI of MS Office IOLE users at the Central University of Technology (CUT). The identified factors will be used to develop a model for guiding designers and developers of IOLE on how to enhance CUI of their software products.

It will be expected of you to complete one online questionnaire at the end of the second term (2018) during one of your practical classes.

This is to state that I, the undersigned (Mr. /Mrs. /Ms.) ___________________, student number ______________ do hereby voluntarily agree to participate in the above-mentioned research study conducted by Miss HA Nortjé from the Central University of Technology, Free State.

The following are conditions of my participation in this study:

- My participation in this study is voluntary.
- I have the right to withdraw from this study at any time.
- I understand that this does not test my capabilities, but the system in question.
- I will not be paid for taking part in this study.
- All the information collected from me during this study will only be for research purposes.
- All my personal information will remain confidential and no information that identifies me will be published.
- I will respond to all the study questions as honestly as possible.

I understand and accept this agreement after I have carefully studied the above.

Signature of participant ______________________ Date: ______________________

Name (in print please) ______________________

Appendix C: Origin models of MIQ items

Potential factor	Item code	Item	Source
Confirmation	CF1	My experience with using SAM was better than what I expected.	Bhattacherjee (2001)
	CF2	The service level provided by SAM was better than what I expected.	Bhattacherjee (2001)
	CF3	Overall, most of my expectations from using SAM were confirmed.	Bhattacherjee (2001)
Continuous use Intention	CUI1	I intend to continue using SAM rather than discontinue its use.	Bhattacherjee (2001)
	CUI2	My intentions are to continue using SAM than using any alternative means.	Bhattacherjee (2001)
	CUI3	I will use the e-learning system on a regular basis in the future.	Bhattacherjee (2001)
Information Quality	IQ1	SAM provides correct and accurate information.	H. J. Chen (2010)
	IQ2	SAM provides complete and sufficient information.	H. J. Chen (2010)
	IQ3	SAM provides precise and clear information.	H. J. Chen (2010)
	IQ4	The information provided by the SAM meets my needs.	H. J. Chen (2010)
	IQ5	The information provided by the SAM helps to solve my problems.	H. J. Chen (2010)
Perceived Ease of Use	PEOU1	Learning how to use SAM is easy for me.	Thong et al. (2006)
	PEOU2	My interaction with SAM is clear and understandable.	Thong et al. (2006)
	PEOU3	I find SAM easy to use.	Thong et al. (2006)
	PEOU4	It is easy for me to become skilful at using SAM.	Thong et al. (2006)
Perceived Usefulness	PU1	Using SAM can improve my learning performance.	Bhattacherjee (2001)
	PU2	Using SAM can increase my learning effectiveness.	Bhattacherjee (2001)
	PU3	I find SAM to be useful to me.	Bhattacherjee (2001)

	PU4	Using SAM increases my learning productivity	Bhattacherjee (2001)
	S1	Using SAM is enjoyable.	Thong et al. (2006)
Satisfaction	S2	Using SAM is pleasurable education.	Thong et al. (2006)
	S3	I am pleased with the experience of using SAM.	Bhattacherjee (2001)

Higher-order potential factor	**Item code**	**Item**	
	TD1	Time appears to go by very quickly when I am using SAM	Agarwal & Karahanna, (2000)
	TD2	Sometimes I lose track of time when I am using SAM	Agarwal & Karahanna, (2000)
Time Distortion	TD3	Time flies when I am using the SAM	Agarwal & Karahanna, (2000)
	TD4	I end up spending more time than I had planned on SAM	Agarwal & Karahanna, (2000)
	TD5	I often spend more time on SAM than I had intended	Agarwal & Karahanna, (2000)
	CT1	When using SAM, I feel in control.	Agarwal & Karahanna, (2000)
Control	CT2	I feel that I have control over my interaction with SAM	Agarwal & Karahanna, (2000)
	CT3	SAM allows me to control my computer interaction	Agarwal & Karahanna, (2000)
	I1	I become unaware of my surroundings while using SAM	Agarwal & Karahanna, (2000)
	I2	I temporarily forget worries about everyday life while using SAM	Agarwal & Karahanna, (2000)
Immersion	I3	While using SAM, I am able to block out most other distractions.	Agarwal & Karahanna, (2000)
	I4	While using SAM, I am immersed in the task I am performing.	Agarwal & Karahanna, (2000)z