Investigating Student Perceptions on Effective Use of Smartphones for Mobile Learning

Submitted in fulfilment of the requirements of the degree of

MICT

In the Faculty of

Accounting and Informatics

at the Durban University of Technology

Esavanie Naicker (19251021)

Date Submitted: 14 August 2019

DECLARATION

I, Esavanie Naicker, declare that this dissertation is a representation of my own work both in conception and execution. This work has not been submitted in any form for another degree at any university or institution of higher learning. All information cited from published or unpublished works have been acknowledged.

[redacted]

Esavanie Naicker

13/08/2019

Date

Approved for final submission

[redacted]

Supervisor

Prof Oludayo O Olugbara (PhD)

14/08/2019

Date

ACKNOWLEDGEMENTS

First of all, I thank God, the Almighty with all of my heart for strength, guidance and inspiration.

I am greatly and sincerely indebted to my supervisor, Prof Oludayo O. Olugbara, for his guidance and support, valuable advice, wisdom and suggestions throughout the research, analysis and write-up process of my research. Completion of this research would not have been possible without your invaluable time, patience, and mentoring. Thank you for providing me opportunities to learn and improve my knowledge.

I also wish to extend my thanks to Mrs Kesarie Singh (ex-HOD at Department of IT), for her support, encouragement and motivation.

I would like to thank Seena Joseph, who always supported me with her valuable discussions, knowledge and guidance.

I would also especially like to thank my colleagues Subashnie, Fiona, Priya, Pragee, Nan, Anusha, Lavanya, Xolile, and Parivash for your support and encouragement in my journey, and reminding of my goal when things got unbearable, and stressful. When frustration, and distractions took me off the road to reaching my goal, you influenced and encouraged me to stay the course. I would also like to thank fellow staff (too many to individually name) at the IT Department for their best wishes, and support as well as the IT students who willingly participated in this research and wished me well.

Finally, and most importantly, I dedicate this dissertation to my family. Firstly, to my husband, Sebastian, and son, Luveshan. Without your love, patience, unconditional support, and constant encouragement this work would not have been possible.

A special acknowledge goes to my late father, Stanley Maistry, for providing me with his heavenly guidance and strength. Much appreciation go to my mum, Visalutchmee Maistry, who has constantly supported and helped in making my daily load much lighter, as well as not forgetting my other extended family members.

TERMS / ABBREVIATIONS

ICT	: Information Communication and Technology (ICT)
TPB	: Theory of Planned Behaviour
TAM	: Technology Acceptance Model
WST	: Will, Skill and Technology
e-learning	: Electronic learning
SMS	: Short Message Service
TRA	: Theory of Reasoned Action
App	: Application
MLMSs	: mobile learning management systems
SEM	: Structural Equation Modelling
PE	: Performance expectancy
EE	: Effort expectancy
SI	: Social influence
FC	: Facilitating conditions
PU	: Perceived Usefulness
PEOU	: Perceived Ease of Use
SN	: Subjective Norm
IT	: Information technology
m-learning	: Mobile learning
UTAUT	: Unified Theory of Acceptance and Use of Technology
EFA	: Exploratory Factor Analysis
CPA	: Principle Component Analysis
SEM	: Structural equations modelling
CFA	: Confirmatory Factor Analysis
CR	: Composite Reliability
AVE	: Average Variance Extracted
VIF	: Variance Inflation Factor
SMSR	: Standardised Root Mean Square Residual
NFI	: Normalised Fit Index
TVET	: Training and Vocational Education and Training

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ABSTRACT

The current trend in educational institutions worldwide is the use of smartphones and smart devices to enhance student learning, which has many intrinsic benefits in improving students learning abilities, academic success, and engagement. The important features of education mobile applications boost student engagement through skills-oriented activities. It makes learning ubiquitous, provides access to the latest assorted learning materials, and reduces the communication barrier between students and education institutions. However, many important factors must be taken into account for the successful implementation of mobile applications by the mobile learning industry. This work investigates the factors influencing student perceptions of effective use of smartphones for mobile learning, by exploring theory of planned behaviour, technology acceptance model, expectation confirmation model, flow theory, and will, skill and tool model. A new structural model has been developed based on the factors satisfaction, continuous intention and effective use that can be applied to explain the effective use of smartphones for mobile learning. Data were collected from a survey population that represents 569 students studying at the university to validate the developed model. The technique of variance-based structural equation modelling was used for testing both the measurement and structural models to establish the full predictive power and reliability of the developed model. The results obtained are highly encouraging, giving predictive capability, reflecting that satisfaction and continuous intention to use are the most important predictors of the effective use of smartphones for mobile learning. These capabilities will enhance student learning skills to achieve better academic success through the exploration of the effective use of smartphones for mobile learning.

CHAPTER 1: INTRODUCTION

1.1 Background

Mobile learning, otherwise known as m-learning or ubiquitous learning (u-learning), refers to 'learning on-the-go', at any conceivable place or time, using mobile or smart devices. Mobile technology requires the use of mobile electronic devices such as smartphones, iPads, tablets, laptops, or emerging virtual reality devices. M-learning, as an educational technology, has become of paramount importance in almost all educational levels, including tertiary education. It has increased the value of electronic learning (e-learning), by combining it with personal computing devices that enable unrestricted acquisition of learning information in terms of time, and at any geographical location (Al-Emran, Elsherif and Shaalan 2016). However, unavoidable constraints such as internet access problems caused by inferior technological infrastructures, insufficient access to modern mobile devices, and a deficiency in m-learning pedagogical skills create bottlenecks for effective m-learning (Kaliisa and Picard 2017).

Smartphone technology has been invented to increase access to the internet by combining the capabilities of telephones and personal digital assistants or a computers to send email, receive email, edit documents and connect to the internet in order to offer personalised services. A smartphone is a handheld, portable personal computer that possesses remarkable processing power capabilities, such as high-speed access to the internet using both wireless networking (WiFi) and mobile broadband. Smartphones use a mobile operating system like Android, Symbian, iOS, BlackBerry OS, or Windows mobile, which enable it to process a variety of software components, also known as "Apps". Smartphones are those ubiquitous and portable devices popular among many users, including students. According to the Pew Research Center (2015), the ownership rates of smartphones in emerging and developing nations of the world are rising substantially. The extensive use of smartphones has provided unique opportunities that constitutes better and improved learning experiences for students (Arain et al. 2018). In particular, the transition from secondary school education to university education is not usually smooth, but proves a huge jump for many students (Van Zyl, Gravett and De Bruin 2012). Most students tend to struggle in their first year, as they are undecided and cannot easily adapt to greater workloads, different teaching methods, independent learning, no appropriate textbooks, and a lack of availability of computer laboratories, which constitute some of the challenges they have to face. Consequently, m-learning through the use of smartphones can help alleviate most of these challenges.

1.2 Problem Statement

M-learning can reach greater heights in teaching and learning, but its primary goals are not achieved currently, nor is m-learning widely implemented by academic as yet (Hargis et al. 2014). Despite the increase in the use of smartphones amongst students for social activities such as communication, gaming, and internet search, its effective use as a potential platform for mainstream educational purposes has been slow (Alrasheedi and Capretz 2018). Moreover, a high percentage of students use their devices for different activities, such as messages, emails, internet browsing, or for watching pornography and games, rather than for academic activities. Consequently, more effort is needed to determine the factors that affect the intention of students to use their mobile devices in learning (Ali and Arshad 2017; Hamidi and Chavoshi 2018; Saroia and Gao 2018; Qian and Qian 2019). Although there has been much investigation on the utilization of mobile devices for children in preschool, primary schools, secondary schools and even in some universities, with both positive and negative results, little emphasis has been placed on examining student satisfaction, with the effective use of smartphones for m-learning thereby providing a gap (Carlson-Bancroft and Boogart 2014; Sulaiman and Dashti 2018; Almaiah and Alismaiel 2019). It is perceptible from the literature that there is no clear understanding of factors that influence the low adoption rate or effective use of smartphones for m-learning.

1.3 Research Questions

This study is directed by the following research questions, much arise from the problem statement on the effective use of smartphones for m-learning:

1. What are the identified factors influencing the effective use of smartphones for m-learning?
2. What are the relationships between the identified factors influencing the effective use of smartphones for m-learning?
3. What model can be developed to better predict or explain the effective use of smartphones for m-learning?

1.4 Research Aim and Objectives

The aim of the study is to examine the precursors of the effective use of smartphones for m-learning.

To achieve this particular aim, a number of specific objectives are stated as follows:

1. to identify all possible factors that influence the effective use of smartphones for m-learning;
2. to identify the relationships between the identified factors influencing the effective use of smartphones for m-learning; and
3. to develop a model that better explains the factors that predict the effective use of smartphones for m-learning.

1.5 Theoretical Frameworks

The theoretical framework, which is one of the most important characteristics in the research process, is the structure that supports the theory of a research study. The theory is important in directing the reasoning and acting in the selection of a research topic, development of research questions, conceptualisation of literature review, and solution design approach, as well as an analysis plan for the dissertation study. Theories are formulated to explain, predict and understand phenomena, and in many cases to challenge and extend existing knowledge within the limits of critical bounding assumptions. The theoretical framework of this study is based on the Expectation-Confirmation Model (ECM) of IT continuance (Bhattacherjee 2001), Theory of Planned Behaviour (TPB) (Ajzen 1991), Technology Acceptance Model (TAM) (Davis 1989), Flow theory (Lee 2010) and Will, Skill and Tools (WST) theory (Knezek and Christensen 2008).

ECM is based on users' continuance intention, which is determined by their satisfaction with the use of their specific Information Systems (IS). TPB predicts that actual behaviour is determined by considering the attitude, subjective norm and behavioural control. TAM predicts that the use of a system is directly influenced by perceived ease of use, perceived usefulness, and attitude towards using the system. Flow theory describes the state in which users forget about the surrounding environment. The WST theory predicts the level of technology integration as a function of attitude, competence and access to technology, which are necessary components for the effective integration of technology into the teaching and learning environment of the classroom. However, (Burton-Jones and Grange 2013) have proposed that the use of a system is not beneficial enough, but needs to be effective to achieve a goal.

This study investigates the use of a combination of the theoretical frameworks of ECM, TPB, TAM, Flow Theory, and WST theory to determine the factors influencing student perceptions of smartphones for m-learning. In particular, in this study, the following factors from the abovementioned frameworks were investigated to study the perceptions of students on effective use of smartphones for m-learning: expectation; satisfaction; confirmation; perceived usefulness; perceived ease of use; skill/competency; attitude; subjective norm; perceived behaviour control; intention to use; continuous intention; concentration and actual/effective use.

1.6 Study Contributions

This research study contributes substantially to the body of knowledge in the information systems literature.

1. The detailed analysis of the existing tehnology acceptance models in the information system research is an important contribution of this study.
2. The application of the structural equation modelling technique to explore the existing factors from the well known models of technology acceptance is an important contribution of this study.
3. The development of a new model based on the factors of user satisfaction, continuous intention, and effective use of smartphone for mobile learning is an important contribution of this study. It was found that user satisfaction and continuous intention constitute two important predictors of effective use of smartphones for m-learning.

1.7 Synopsis

The structure of this dissertation can be outlined succinctly as follows. Chapter 1 presents the research problem. It discusses the research questions, research aim of effective theoretical frameworks upon which this study is founded as unique contribution to this study. Chapter 2 provides a comprehensive literature review on the use and adoption of mobile technology. Chapter 3 presents the conceptual frameworks used in this research in exploring factors influencing student perceptions on the effective use of mobile technologies. Chapter 4 presents the methodologies used in this research in exploring factors influencing student perceptions on the use of mobile technologies. Chapter 5 consist of the presentation of analysis and findings of the quantitative survey method for this study whereby the results are discussed. Chapter 6 presents a summary of that which the research had achieved with regard to understanding student perceptions of the effective use of a smartphone for m-learning, limitations, recommendations and a conclusion.

CHAPTER 2:

LITERATURE REVIEW

This chapter reviews literature by researchers in the mobile technology field. The chapter covers the following major areas: perception studies; the student perceptions of m-learning; and the measurements of perceptions. Technology is forever improving and changing. There is a need to understand an individual's choice and feelings. This allows for the creation or development as well as the improvement of technologies. Much research has gone into the perceptions of individuals in Information Communication and Technology (ICT).

2.1 Perception Studies

Perception studies have been used to gain an understanding of an individual's thoughts and feelings. For decades, many studies have looked at the attitude, use, and adoption of ICT in the learning environment. Some of the theories used to study perception are the Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and sometimes a combination of these different theories. TPB shows that actual behaviour is determined by taking into consideration one's previous intentions, along with their values. Behavioural intention could be determined by considering both the attitude towards actual behaviour, and the subjective norm associated with the behaviour (Fishbein and Ajzen 1975). The Technology Acceptance Model (TAM) predicts that the actual system features and capabilities directly influences the use of the system (Davis 1989). UTAUT examines ways to explain user intentions to use an IS (Information Systems) as well as successive usage behaviour (Venkatesh et al. 2003).

2.1.1 E-learning to M-learning

Studies into mobile technology also brought about a need for improving and better performing tasks and methods of learning. Electronic learning, also referred to as e-learning consisted of the availability of electronic content made available to students in a blended learning environment within the classroom. Abdulrazzak (2013) has stated that students discovered that the use of e-learning to be rather effortless, and also made the learning process simple. According to (Park 2009), although attitude positively influenced the intention to use e-learning, a need for utilising automated information away from the classroom has extended e-learning, by introducing m-learning. (Nedungadi and Raman 2012) have highlighted the difference, which is that m-learning can be accomplished in laboratories, the home, or anywhere else, and can be used for longer periods of time, due to its portability, ubiquity and location awareness, whereas e-learning can only take place in a laboratory. (Ally and Prieto-Blázquez 2014) reported that high-level learning results when the student has the opportunity to learn anywhere and is at the center of learning. This is indicated by the vast educational resources freely available and affordable for those eager to learn. However, (Jan *et al.* 2016) have stated that m-learning removes some of the shortcomings of the traditional learning approach, which involves the face-to-face delivery of limited content to a limited number of students occurring during a specified time, as well as that of e-learning, where a student needs a laptop and internet to a specific connection point. M-learning only requires a mobile device that provides affordable and easily available educational material. Therefore, students do not have to wait for specific times and location to learn, which links with m-learning's goal of improving communication and inspiring a student's learning experiences.

2.1.2 Contextual studies on m-learning

(Khan *et al.* 2015) have stated that m-learning adoption is not only affected by country-specific, but also individual constraints, as highlighted by critical reviews of some educationally advanced countries. Much research on m-learning has been conducted in various locations of the world from the time of its inception, and is still ongoing, as there is much importance and need for sustainable growth in education. Mobile devices in learning environments have been effectively employed by a few countries, such as Malaysia, Singapore, Australia and Asia, as well as European Union (Sarrab, Al Shibli and Badursha 2016).

(Gikas and Grant 2013) have explored mobile device usage and implementation in higher education, not only showing student participants' identified shortcomings, but also acknowledging student's learning changes, where students are shown to be able to interact with content by means of social media usage with their mobile computing devices. Research began with the use of SMS technology as collaboration tools for m-learning (Motiwalla 2007), then continued to explore the use of applications (Apps) by teachers in impacting on learning (Domingo and Garganté 2016), and moved on to studies by (Briz-Ponce *et al.* 2017) highlighting the different determinants affecting mobile technology use by undergraduate medical students for learning. Studies conducted on attitude about m-learning revealed a need for m-learning to be explored more intensively on the improvement of communication and enrichment of learning experiences so as to provide increased access to effective teaching and learning at a time convenient to both teachers and students (Al-Emran, Elsherif and Shaalan 2016; Jan et al. 2016; Bhovi 2018). On the other hand, most studies have focused on accepting m-learning as it is still an emerging technology only (Sarrab, Al Shibli and Badursha 2016; Hao, Dennen and Mei 2017; Iqbal and Bhatti 2017; Sharma, Sarrab and Al-Shihi 2017; Hamidi and Chavoshi 2018). Park, Nam and Cha (2012) conducted studies on the factors influencing the acceptance of m-learning, while Kim, Lee and Rha (2017) examined the factors that affected the intention to use and struggle by university students on using m-learning. (Han and Shin 2016), however, presented more positive feedback on the factors that influences learning effects on the students' academic achievement in conjunction with the adoption of mobile learning management systems (LMSs) on mobile device usage by students in tertiary education. Mobile LMS usage has positively influenced academic success of online students. However, this result might not necessarily be the same for students that are part of the on-campus higher education learning environment.

A study was undertaken at a Nigerian university by (Adesoji 2011) on using m-learning to facilitate access to sources of information and services in order to improve accessibility, productivity and excellence in learning. A study on the use and adoption of m-learning in higher education was assessed for behavioural intention of students was conducted by (Mtebe and Raisamo 2014). Studies by (Mutono and Dagada 2016) found that although there is confirmation of an extensive use of mobile technologies in the educational environment in South Africa, students are still very ignorant in relation to m-learning. Students are aware of m-learning, and their prior usage of e-learning has led to students having a more positive attitude towards the use of m-learning, however, most students prefer to utilise their mobile devices for different activities other than learning purposes (Ali and Arshad 2017). (Kaliisa and Picard 2017) highlighted that the huge number of m-learning projects and studies in the African region indicating the popularity of mobile phones or devices for m-learning, and also stated that Taiwan has quite an advanced telecommunication networks. These findings imply that m-learning success and the support of mobile device usage is mainly dependent on developing a stable telecommunication network.

2.2 Learning Resources

Students have made use of electronic resources (videos, text, applications, etc.) available from different locations by individual and groups of students. There have been group learning by means of collaborating with each other via their mobile devices about different subject matters in different areas of study. They have used different types of mobile devices to reap the benefits of improving their learning skills and gaining knowledge at different level of education that is schools, universities as well as the workplace. Teachers too have made efforts by preparing and making available electronic material to assist in the learning needs of their students.

2.2.1 Learning Environment

Mobile technology has allowed students the ability to learn at any location, namely the classroom, home, or on travel excursions. (Iqbal and Bhatti 2017), have indicated that blended learning (a combination of on-campus and online learning) is more effective and contributes positively to a well-rounded student-centred experience. There have been studies on individual m-learning in the classroom as well as group m-learning. Research was conducted by (Henderson and Yeow 2012) to determine the reaction of teachers and students with regards to iPads focused on mobility, student engagement and collaboration. Tavallaee, Shokouhyar, and Samadi (2017) have highlighted that in-field learning activities help students to take note of, recognise, and distinguish characteristics of the objects of the real-world, as well as become more familiar with their mobile device while m-learning. According to (Melero, Hernández-Leo and Manatunga 2015), students sharing a mobile device showed that their performance was unaffected however students making up large groups felt left out as they were not in possession of the mobile device.

2.2.2 Courses

Mobile technology has been used to learn different subject matter. A study conducted by (Carlson-Bancroft and Boogart 2014) introduced iPads in primary schools to enable children, including special needs learners in reading, writing and content skills aimed at helping learners with different learning needs. Students' academic performance at schools has been positively influenced with the implementation of iPads. A review by (Kagohara *et al.* 2013) also noted the use of mobile devices by individuals with developmental disabilities for a variety of purposes, especially improvements in education, collaboration, entertainment, gaining skills for the workplace, as well as transitioning skills. However, the focus of study was on younger age group students, and on severe disabilities, rather than on older students with multiple disabilities. (Ostashewski and Reid 2010) have stated that iPad usage was successfully implemented in the teaching and learning of Music. However, studies by (Teri *et al.* 2014) on the usefulness of LMS applications by biochemistry students did have some negative outcomes, as not all students were keen towards m-learning utilization. A study by (Kutluk and Gülmez 2014) has determined that the m-learning perspectives of university accounting students tend to differ on their views of mobile technology, as students were interested, though have not used mobile devices effectively due to not having technological support for their content. They are of the view that m-learning can only be effective if they are provided reliable service and easy navigation through content. A study by (Hargis *et al.* 2014) focused on m-learning using applications to learn Maths and English. The study revealed a positive response to technology knowledge, instruction, and content. Students enjoyed the technological use for learning, becoming more independent students, as well as increasing informal learning. In addition to this, teachers experimented in order to find ways of effectively implementing the iPads.

Studies by (Engel, Palloff and Pratt 2011) have also found that distance students use and appreciate m-learning. (Alyahya and Gall 2012) conducted an investigation on the use of iPads by mature Master's and PhD students for study, research, and assignments. Students felt that these devices made studying easier, because they could work in between doing other things, which ultimately saved time as well as being a good planning and time management tool. However, students were not using all of the capabilities of the iPad that were available, which would have been helpful for doing both assignments and projects. According to (Alrasheedi and Capretz 2018), professional individuals also use features of m-learning in the workplace. This enables employees to apply their knowledge immediately after learning a specific concept or subject, instead of learning and storing the information and using it years later; which may have become obsolete as technology changes. According to (Byrne-Davis *et al.* 2015), a huge number of students perceived that mobile device use impacted on their education, and had become a part of their workplace learning, which can be successfully implemented and evaluated in medical education for just-in-time technologies. (Briz-Ponce *et al.* 2017) showed how undergraduate medical students used mobile technology for learning, (Archibald *et al.* 2014) investigated the learning and teaching perceptions in the field of medicine. Studies were conducted on the course syllabus, assessments, ease of use, portability, applications used, resources available, and the perceptions on mobile devices for instructing and studying. It was found that the iPad did improve student performance, as well as the quality of teaching.

2.2.3 Devices

For studying to transpire at any point in time as well as at any location, mobile devices are a requirement or a necessary tool. Mobile devices, comparatively cell phones, smartphones, iPads, tablets, and even laptops use mobile technology which can be used at any location. Cell phones are electronic devices, but with limited features. Specific studies have directed attention about the using cell phones for m-learning. (Motiwalla 2007) evaluated m-learning using cell phones focusing with the satisfaction of e-learning systems to m-learning systems. The research conducted by (Ekanayake and Wishart 2015), on the other hand, used cell phones to teach science teachers to use and design online learning material. A smartphone is a cell phone, but with many more features and functionalities. A study by (Ali *et al.* 2015) used a conceptual framework to determine the usability of smartphones whereby students experienced satisfaction with the user-friendliness of the device and a study conducted by (Koo, Chung and Kim 2015) specifically used smartphones for m-learning, but focused more on the user competence of the device and found that the device was also underutilised. The iPad is an Apple tablet using the iOS mobile operating system, which is also quite expensive, but (Alyahya and Gall 2012) found that the iPad was the preferred device used for learning and studying on the move, even though it was not utilised properly. The Apple iPad came out in 2010, and was very effective in m-learning. The study by (McCombs and Liu 2011) indicated that the use of iPads was useful and enjoyable, and the preferred device compared to laptops for learning purposes. This device was also evaluated by (Melhuish and Falloon 2010) for its portability, use for collaboration, and easy interaction, but even though many students still like smartphones, and being able to learn in a fun and easy way, there are still problems with its use for m-learning. (Henderson and Yeow 2012) mentioned that some teachers lacked the necessary control and skills in the use of iPads, and some students also had skills and distraction issues, even though they enjoyed using the iPads when compared to the laptops which, according to students, were not as mobile or portable. Also, the true potential of the use of the iPad was not demonstrated which, according to (Mang and Wardley 2012), could also be said for tablets. Students participated in a discussion on the submitted work by means of comments, which prevented them from being isolated. Feelings of isolation could have occurred due to them feeling either uncomfortable, or shy, with regard to face-to-face learning. The collaboration between students was quite exciting and successful.

According to (Haßler, Major and Hennessy 2016), a tablet device is a combination of multiple characteristics, including easy customisation and portability, as well as high-quality touch interfaces. Applications designed for tablets are simpler and easier to use when compared to laptops, which consist of computer programs that are more traditional. The reason for this is that tablet applications are designed to work with a different screen sizes, and lack the feel of opening and closing applications, or of saving data. This has the educational advantage of simplicity for faster learning, and the limitation of compact functionality and less customisability. An additional factor is its ability to work with cloud storage. (Engel, Palloff and Pratt 2011), however, highlighted the benefits of increased informal learning, as well as the mobility of the learning device experienced by students, where they were allowed to use any type of mobile device for m-learning. (Teri *et al.* 2014) examined m-learning utilization by biochemistry students. Students used smartphones, tablets, as well as computers. A study by (Al-Emran, Elsherif and Shaalan 2016) argued that tablets, as well as smartphones, has greatly encouraged students to enhance their learning by incorporating their mobile devices. This result could be associated to the ownership of mobile devices by a much larger number of students when compared with those who do not own mobile devices. (Kaliisa and Picard 2017) have said that mobile phones constitute a popular type of mobile devices for m-learning purposes, used by instructors as well as students, which suggests that student learning in higher education contexts can be supported by mobile devices.

2.2.4 Teachers

When examining the teacher perspective on the use and learning of applications via the tablet, (Prasertsilp and Olfman 2014) found that teachers were reluctant to use such a technology in the classroom. This study, therefore, sought to encourage, motivate, increase teacher competency as well as teacher attitude towards mobile technology. The study conducted by (Carlson-Bancroft and Boogart 2014) to determine teacher's attitudes and viewpoint regarding iPad implementation for m-learning resulted with different instructions being required for different teaching and learning opportunities. (Hargis *et al.* 2014) conducted research on teacher and student use of iPads noting that teachers were not *au fair* with technology and assessments, and the content taught were not aligned. (Gikas and Grant 2013) stated that instructors were also anti-technology, and should provide effective ways of executing learning on these devices, even though students are the driver of technology integration. (Henderson and Yeow 2012) have meanwhile argued that behaviourism teaching was used as opposed to constructivism, as students were not allowed to create their own content, which did not support learning, but improved productivity and accessibility of resources in the classroom. Behaviourism can be understood as the learning of a set of material, being tested on it, followed by the learning of the next set, testing, and so on; as compared to constructivism, whereby a student learns from the experience of doing a particular task as well as interacting with other students (Bada and Olusegun 2015). Behaviourism made teaching simpler, as students became intuitive with technology. (Domingo and Garganté 2016) directed an investigation on instructor perceptions while using a number of specific apps in the classroom for m-learning. This suggests that facilitating information access and commitment in learning impacts on mobile technology. Findings have also shown that the instructors' observation on the impact of mobile technology in learning depends on the choice of apps.

Research conducted by (Ekanayake and Wishart 2015) used cell phones to teach science teachers about placing learning material online. The teachers were grouped so that they could develop classroom lessons that will be taught in the classroom. Even though the attempt has been successful as a once-off lesson, teachers experienced very limited time to learn to use the devices and their inexperience was also not taken into account. According to (Al-Emran, Elsherif and Shaalan 2016), instructors also had positive attitudes towards m-learning as they owned smartphones, tablets, or smartphone and tablets, with a majority owning smartphones. The instructors had also shown proficiency in using their devices. On the other hand, (Kaliisa and Picard 2017) found that instructors were not aware of the capabilities of their devices. As per the review by (Kaliisa and Picard 2017) the issue of teacher perceptions showed that whilst some instructors were very innovative in implementing and integrating technology into the classroom; others have refused to try out any new technology. In addition, instructors felt that the purpose of mobile device integration in the process of instruction was affected by a lack of knowledge and skills in designing course curriculum and assessments. The review also stated that instructors felt apprehensive that private information would be made visible to students. According to (Sharma, Sarrab and Al-Shihi 2017), instructors find it difficult to adjust to this new development of m-learning, and this is made evident by students and instructors.

2.3 Student Perceptions of M-Learning

Learning is a fundamental aspect of any student's life and, in order for m-learning to be a success, a proper understanding of student perceptions on m-learning benefits and challenges are necessary.

2.3.1 Benefits

The following consist of some benefits of using m-learning:

a) *Access*: According to (Jacob and Issac 2008), students consider m-learning to be another way of learning with easy content retrieval. Furthermore, it encourages learning without geographical limitations. (Caudill 2007) states that m-learning takes place at any location as opposed to traditional learning (face-to-face or teacher to student) or e-learning. M-learning provides an interface to content that is both personalised, and secure, which is not on a public machine (Caudill 2007). M-learning delivers a flexible, easy to access learning resource for the student's specific needs, as it is not time-consuming, thus students will not be demotivated to access the environment (Caudill 2007). According to (Melhuish and Falloon 2010), mobile devices provide portability, easy accessibility to e-books, articles, documents, and notetaking, with (Alyahya and Gall 2012) highlighting the fact that students had continuous access to their iPads. A study by (Mtebe and Raisamo 2014) also found that some students in higher education institutions had adequate knowledge and resources to use mobile devices for learning purposes.

b) *Convenience*: It provides learning to take place anywhere, without needing to bring in bulks of books or learning materials. Also, it provides quick access to information (Gikas and Grant 2013); instructional flexibility in order to present learning at the individual's desired time and place (Hamidi and Chavoshi 2018); and if some students are not able to attend the class, they still have access to lecture materials (Jacob and Issac 2008). A review by (Kaliisa and Picard 2017) indicates that cellular telephones can enhance learning and lead to a sense of ambient co-presence and continuous availability among students. According to (Jan *et al.* 2016), large numbers of students who are unable to access the traditional learning system due to their location and various socioeconomic factors, may access learning materials from anywhere and anytime using their mobile phones. (Byrne-Davis *et al.* 2015) found that medical students were using iPads to make use of previously difficult-to-use time, e.g. waiting for clinics to begin.

c) *Fun*: (Alyahya and Gall 2012) highlighted students' excitement at taking pictures, and preparing presentations with iPads for their assignments. (Kaliisa and Picard 2017) also mentioned that m-learning makes learning more enjoyable, flexible and interactive since students are not rendered immobile by the restrictions of desktop computer technology or the traditional classroom settings.

d) *Usefulness*: Mobile devices are widely used and have become a necessity nowadays even though some may consider it a luxury. Students believe that they have entered into an era of technology, and would drop out if they were not up to date with it. They also believe that it might help them to expand their knowledge and live towards the new technology (Jacob and Issac 2008). The review by (Kaliisa and Picard 2017) reports that university students' perceptions of mobile technology use in the UK found that students tend to choose technology based on the extent to which it improves their learning. Also, studies reviewed by (Kaliisa and Picard 2017) showed that students are willing to use and adopt mobile devices and mobile apps, especially where provisions for bigger screens, keyboards, as well as better processing power are made, thereby making it simple to use for learning purposes.

e) *Learn at own pace*: (Jacob and Issac 2008) reported that m-learning ought to be considered as a way of supporting teaching in the class, that is, as a supplement to learning. Students would be able to repeat the lecture again and again to enhance their understanding. This allows students the flexibility of finding answers their own way, depending on what they are learning, as different students are in different fields of study, and it also provides any number of ways to learn (Melhuish and Falloon 2010). According to (Archibald *et al.* 2014), brighter students were able to get other applications to enhance their learning. (Gikas and Grant 2013) show a variety of ways to learn, also enabling situated learning in which students learn naturally in real life contexts.

f) *Collaboration*: Melhuish and Falloon (2010) have stated that it enables people to converse with each other, and Alyahya and Gall (2012) mentioned that it provides fast internet access by means of emails, videos, sharing of information sites with other students, as well as being able to plan and organise their time. It allows for communication and content collaboration to take place (Gikas and Grant 2013), especially allowing for effective communication between teacher and student (Ali and Arshad 2017), and an increase in two-way interactions (Hamidi and Chavoshi 2018). According to (Kaliisa and Picard 2017), the enjoyment of classes made up of a combination of traditional and technology instructing and learning have provided continuous access to knowledge, opportunities for collaboration as well as growing engagement between students. (Hargis *et al.* 2014) observed that students felt empowered by becoming more independent as researchers, due to an increase in student engagement. There was a decrease in the completion time for assignments; students provided help and support to one another; and there was an increase in the number of students around the campus.

g) *Pedagogical benefits*: M-learning provides portability, ubiquity, and location awareness (Nedungadi and Raman 2012). According to (Ali and Arshad 2017), students believe that m-learning promotes an increase in acquiring knowledge. Most students agreed on the fact that m-learning encourages a sense of responsibility and independent learning, thus increasing their confidence and make them more active and involved in creating knowledge.

h) *Cost Effective*: M-learning was less costly as students had easy access to e-books, and sharing of information.

2.3.2 Challenges

The following are some of the challenges of m-learning:

a) *Design/capability issues:* (Caudill 2007) suggested that the content, format of information, user location and the limitations of the user's device must also be taken into consideration. Focus should be on the student and not technology. It will not be beneficial to students if applications are too complicated to use. (Ali *et al.* 2015) have stated that it is vital that m-learning applications are simple to use, that knowledge is easily acquired, comprehensible, as well as appealing to provide a satisfying experience. The user interface depicts the association between the user and the smartphone application, which is important for each individual, where meeting usability needs for the m-learning applications is extremely significant. The technical knowledge of the student needs to be considered as well as technical access of different groups, younger and older generation of students, are different. Mobile networking connectivity enables access to learning material, including updated material. Compared to laptops and computers, mobile devices experience certain technical issues, including the small screen sizes, insufficient storage capacity, having to regularly charge the batteries, different types of hardware, processing power, network access, and other necessary capability issues to be sorted by the m-learning applications developers (Ali and Arshad 2017). M-learning resources must be developed to fit on different screen sizes. (Bluestein and Kim 2017) have highlighted that technology challenges, which resulted in apps failing without providing any warning and the time wasted when trying to access websites as a result of the internet connection being too slow and/or unreliable. Some students have admitted to their own failure in remembering to properly charge the device before class or in some cases forgetting to carry a charger for their device. (Kaliisa and Picard 2017) stated that internet access problems is based on poor technical infrastructure, modern mobile device access, deficiency in m-learning educational competence and the prevalence of a undesirable attitude among instructors and management leaders of institutions on m-learning. Mobile devices are very slow, requiring larger memory. The review also included findings by Mayisela (2013) on the rise in already high internet costs, access to learning resources being restricted, as well as the unsuitability of mobile devices with the university learning management systems. Reviews by Kaliisa (2017) also reported that the challenges of mobile devices for learning purposes included network/bandwidth failures, power shortages, limited knowledge in the use of smart mobile devices, lack of internet enabled/smart mobile devices among both students and lecturers, and the absence of policies guiding the use of mobile devices for learning.

b) *Device Ownership*: A study by (Jacob and Issac 2008) showed that not every student owns electronic devices as they are expensive and students had negative feelings towards its support regarding their studies. Also, (Alyahya and Gall 2012) mentioned that there were still a lot of students who could not afford mobile devices. A further complication reported by (Henderson and Yeow 2012) was the domination of shared device when a device was loaned to groups of students.

c) *Distraction*: Electronic devices were a distraction (Gikas and Grant 2013) and caused students to lose concentration and entertain themselves, which would aggravate the problem if other than "attending class", they are somewhere doing something they prefer (Jacob and Issac 2008). (Henderson and Yeow 2012) have highlighted that teachers have less control over students as there is the possibility for students being distracted with non-schoolwork related applications such as chatrooms, instant messages, games, inappropriate sites, cheat tests, etc. On the other hand, Rambe and Bere (2013) stated that mature students felt that after class group discussions was a distraction to their family lives. (Bluestein and Kim 2017) said that students agreed that they used the devices more for non-academic purposes than they expected they would. According to (Hargis *et al.* 2014) students are not able to work on their own unless they were pushed.

d) *Resistance to Change*: Students said that printed documents were most efficient, as these helped them to concentrate better when looking at the paper than at a screen. They said that learning from textbook was even more efficient, as they got detailed explanations, rather than searching elsewhere, such as on the Web (Jacob and Issac 2008). (Henderson and Yeow 2012) highlighted the resistance from teachers to using technology to teach as well as a need for unskilled teachers to be trained. (Teri *et al.* 2014) found that students were not so keen to use m-learning, as they preferred traditional learning. It was also found that the iPads were only used when the desktop was not available (Archibald et al. 2014). According to Bluestein and Kim (2017), students preferred to handwrite their notes.

e) *Lack of skills*: According to Archibald et al. (2014), students had different levels of technology skills or experience (Henderson and Yeow 2012) and not all students may be at ease using technology. This may cause them to feel left out. (Alyahya and Gall 2012) highlighted that students preferred having a workshop on how to fully use these devices. (Hargis *et al.* 2014) reported that more lessons were required. Additionally, (Gikas and Grant 2013) stated that even though some students described themselves as technologically savvy, some technologies still proved challenging to the them.

f) *Management*: Educational institutions did not have the infrastructure on the use of mobile technology for learning that will support teachers and students (Archibald et al. 2014), which requires a proper learning environment, management and facilitation (Henderson and Yeow 2012). (Kaliisa and Picard 2017) highlighted that inadequate m-learning educational skills, the negative attitude towards m-learning by some instructors, as well as institutional leaders not providing sufficient support towards technological infrastructure, resulted in problems with internet access, as well as lack of access to modern mobile devices. (Tavallaee, Shokouhyar and Samadi 2017) stated that the shift from a traditional teaching method to m-learning is quite complex, since this type of learning includes the coordination of students, teachers, contents, institutions, and all beneficiaries with an important responsibility in producing a new way of gaining knowledge. It is of extreme importance that students are motivated too, as the m-learning infrastructure is not the only contributing factor towards the adoption of m-learning. (Khan *et al.* 2015) have indicated that the impact and mobile devices usage for learning must be recognised by m-learning stake holders. Findings on the importance of perceived behavioural control by (Cheon *et al.* 2012) have suggested that various functions of mobile devices for learning ought to be provided by managers of colleges, thereby offering opportunities to learn, an enhancement of perceived behavioural control, as well as an improvement to m-learning attitude by students. Similarly, according to (Kim, Lee and Rha 2017), service providers and educators ought to effectively deliver m-learning to students by exploring and discovering new benefits of utilising m-learning when compared to existing learning approaches.

g) *Unexpected Costs*: Loaned devices required exorbitant additional costs such as the cost for an iPad for each student, software costs, as well as breakage costs that might be required to fix or replace mobile devices. On the other hand, (Bluestein and Kim 2017) have highlighted that students expressed frustration about the lack of overall usage of mobile devices, and unused apps that they downloaded and purchased for the class, as it was difficult to choose the most appropriate application from a very large available range (Henderson and Yeow 2012). The true potential of the use of mobile devices has not been demonstrated (Henderson and Yeow 2012), and not all capabilities were used (Alyahya and Gall 2012). Teachers and students were paying a lot of money daily for internet access to allow them to download learning content, and even so still experienced failed downloads (Adesoji 2011; Mtega et al. 2012).

h) *Security*: It was not practical to carry the device all the time as there was a possibility of loss or theft (Archibald et al. 2014). It is sometimes necessary for students to always carry mobile devices to different locations in order to access information may lead to severe security repercussions (Hao, Dennen and Mei 2017; Hamidi and Chavoshi 2018).

i) *Interface design*: Students felt that the learning management system applications used was not user-friendly. There were difficulties in inputting information into certain field notes (Archibald et al. 2014). (Rossing *et al.* 2012) reported that students were concerned about the stability and design of the applications reporting that the applications had bugs, lacked functionality, and was ineffective.

2.4 Measures of Perception

Studies conducted on student perceptions of m-learning showed that research was mostly based on the m-learning usage, differing attitudes towards m-learning, and m-learning acceptance by students.

2.4.1 Attitude

(Al-Emran, Elsherif and Shaalan 2016) examined student and instructor attitudes with regard to m-learning. Most students have positive attitudes towards mobile device use for m-learning and intend to incorporate it into their learning, which is attributed to the ownership of mobile devices by the majority of the students. (Mtebe and Raisamo 2014) reported that access to learning resources, accomplishing learning tasks, communicating and obtaining better grades through the utilization of the university's learning management systems have resulted in students having a positive attitude towards mobile device use. A study by (Arain *et al.* 2018) also suggested that Apps have positively influenced students's learning success. A study by (Almaiah and Jalil 2014) shows that positive perceptions on m-learning and the preferred use of their mobile devices by students for both learning and administrative services. (Bhovi 2018) highlighted that the relationship between the perception and attitude on m-learning activities is positively significant; with (Ali and Arshad 2017) also revealing that those students that have benefitted from using e-learning resources are similarly finding m-learning to be quite valuable as well. (Mutono and Dagada 2016) indicated meanwhile that the use of internet access through their mobile phones has been taken advantage of by a huge number of students.

A third of the participants had knowledge of m-learning and a large number indicated having no idea about the concept. The study finding indicated that m-learning use is supported by students. (Al-Emran, Elsherif and Shaalan 2016) stated that students have improved attitudes to m-learning in higher education, while research by (Rossing *et al.* 2012) has reported that mobile technology provides an extraordinary availability of information with both positive and negative feedback. Comparatively, (Muharrem and Tufan 2016) highlighted that students using tablet computers in class had negative views. The students also stated that the interaction between students and teachers was reduced when utilising tablet computers. A majority of students revealed that learning was not quick and easy, understanding topics was difficult, there was no contribution to the increase of academic success, and learning was temporary when using tablet computers during the teaching process. A large number of students expressed concerned about radiation as well as some other adverse physical effects, such as headaches and eyestrain when studying with tablet computers.

Research by (Briz-Ponce *et al.* 2017) suggests that an important factor when it comes to the prediction of attitude towards technology use is perceived usefulness, which is similar to the result reported by the forefather of the TAM theory, Davis (1989). (Tavallaee, Shokouhyar and Samadi 2017) discovered that the factors perceived behavioural control and behavioural intention influenced the acceptance of m-learning. Students reach the behavioural intention stage when their attitude towards using the device is positive. The factors influences students' attitudes on acceptance of m-learning are perceived usefulness and ease of use. (Han and Shin 2016) reported that the use of mobile devices by online students was better understood when the mobile learning management systems (LMSs) adoption factors and effects of the academic achievement of students were examined. Recent literature by (Iqbal and Bhatti 2017) indicates that blended learning (a combination of on-campus and online learning) is more effective, and contributes positively to a well-rounded student-centred experience. According to (Heflin, Shewmaker and Nguyen 2017) students perceived mobile technology collaborative learning positively, but they did not engage during class.

2.4.2 Use

(Byrne-Davis *et al.* 2015) stated that the use of mobile devices by students impacted on their studying and collaboration with colleagues. (Han and Shin 2016) meanwhile examined factors affecting students academic achievement, as well as mobile learning management systems (LMSs) adoption. Research was conducted by (Kinash, Brand and Mathew 2012) on the perceptions of students using Blackboard Mobile Learn and iPads, where students were allowed to use their own devices, or could get a device loaned to them for a two-week period. Opinions expressed by the students ranged from being very satisfied using Blackboard Mobile Learn, to not being bothered to even use it. Some students felt that it did not make much of an impact to their learning, and was not motivating enough for them, as it was not something that they wanted or demanded.

Many students remained neutral regarding m-learning. (Archibald *et al.* 2014) conducted studies on the insight about the use of iPads for instructing and learning, syllabus and assessment, ease of use, portability, applications and resources. Whilst it was found that the use of iPads did improve student performance as well as the quality of teaching, it was also found that students had different levels of technical skills or experience, and that institutions did not have the infrastructure to support teachers and students. Studies by (Sharma, Sarrab and Al-Shihi 2017) also explored the adoption of m-learning in higher education by measuring the extent to which students respond to m-learning. According to (Bluestein and Kim 2017), students experienced limitations when using the device in class. Gender and age characteristics could be predicting factors for users in forming and accepting new technology, but was not taken into consideration. The main finding by (Mtebe and Raisamo 2014) was that four factors namely “performance expectancy, effort expectancy, social influence, and facilitating conditions” had a remarkable positive influence towards students' intention to use m-learning. Students believe that they will be able use m-learning, as it is clear, understandable and simple.

It was found that students believe they were quite competent to use m-learning and that their colleagues and friends would be able to influence them on using m-learning (Mtebe and Raisamo 2014). (Hao, Dennen and Mei 2017) stated that students were most likely to engage in m-learning when it was educationally useful and simple to use as confirmed by the TAM model. Subjective norm was not considered significant, as students were not concerned with what others were doing but did as they desired. They found that the factors perceived usefulness and perceived ease of use positively influenced the factor behavioural intention, and that subjective norm indirectly influences behavioural intention through its positive influence on perceived usefulness. Their findings also indicated that subjective norm does not influence perceived ease of use. However, studies by (Iqbal and Bhatti 2017), indicate that in online learning environments, individual differences in academic achievement and satisfaction may be explained by key qualities, including computer abilities, technical expertise, attitude towards computers, and learning choices. Social influences, however, did not impact perceived usefulness. Attitude in respect to usefulness is positive and perceived usefulness affected behavioural intention positively.

2.4.3 Acceptance

(Sarrab, Al Shibli and Badursha 2016) reported that very few countries were able to quite effectively engage the learning environment with mobile devices. Furthermore, the findings reveal that the contributing factors include "ease of use, usefulness, enjoyment, suitability, social, and economic factors" on m-learning decisions by instructors and students to accept or reject m-learning is determined by the factor adoption (Hamidi and Chavoshi 2018). Usefulness was positively influenced by ease of use. Trust and the culture of using m-learning positively influenced behavioural intention. The relationships between personal characteristics and behavioural intention as well as ease of use and usefulness with behavioural intention were insignificant. (Tavallaee, Shokouhyar and Samadi 2017) highlighted that the key factors include perceived behavioural control and behavioural intention, leading to the formation of actual behaviour in students and the acceptance of m-learning. The factors "perceived usefulness and ease of use" are important in forming attitude. Attitude and subjective norm are also effective factors in behavioural intention.

(Domingo and Garganté 2016) directed a study on expanding the knowledge on the integration of mobile technology for learning in primary school education by the use of Apps in the classrooms. (Hsiao, Chang and Tang 2016) focused instead on continuance intention rather than behaviour, as it was necessary to explore satisfaction and continuous use of social mobile apps. According to research by (Koo, Chung and Kim 2015) on the exploitative and explorative use of smartphones, perceived usefulness strongly predicts user satisfaction and user satisfaction determines user competence. However, the chances of using systems more innovatively increases the use of the device's many features. The quality and consistency of the information is maintained by the relevance of the information, adequacy, correctness and appropriateness. A study by (Zhou 2014) on internet site users confirmed that the flow experience is affected by the features of the system, as well as information characteristics. Meanwhile, according to a study on online learning by (Dağhan and Akkoyunlu 2016), satisfaction is greatly influenced by the quality of the information.

2.5 Methods of Perception

Perception measurements in the learning environment have been conducted to gain the views and insight of students on mobile technology for learning. The methods used to conduct studies on student perceptions of mobile technology for learning were quantitative, qualitative, as well as a mixture of both quantitative and qualitative, known as hybrid.

2.5.1 Quantitative

Much of the studies reviewed have used a quantitative study and a survey. The questionnaires were mostly used for data collection in order to evaluate if an objective is being achieved. Student perceptions regarding m-learning were conducted in Pakistan by (Iqbal and Bhatti 2017) using a structured questionnaire to gather the responses. The study on m-learning resistance usage by (Kim, Lee and Rha 2017) also used questionnaires comprising multiple items that measured each item consisting of a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). (Briz-Ponce *et al.* 2017) measured student behaviour with mobile technology. The methodology was based on a quantitative survey of medical students at the University of Coimbra using TAM and UTAUT. (Matthews, Hodgson and Varsavsky 2013) conducted a quantitative study of the student perception on the amount of quantitative skills gained academically in science during their study at a university. (Chang, Hajiyev and Su 2017), on the other hand, conducted a study on undergraduate students to determine the factors affecting e-learning usage.

The data collected from 714 undergraduate and masters students was analysed using Structural Equation Modelling (SEM). The study by (Arain *et al.* 2018) compared the learning of two groups of students. The experimental group was made up of traditional classroom learning and the control group used traditional learning and learning through a mobile app. Questionnaires were used as the instrument. Much quantitative research was done on the perceptions of using m-learning. In all cases the survey instrument used to measure was a questionnaire with Likert scales. (Teri *et al.* 2014) studied m-learning by biochemistry students. The data collected by (Tavallaee, Shokouhyar and Samadi 2017) were the result of an online questionnaire which measured items on a seven-point Likert scale, ranging from 'totally disagree' to 'totally agree'. Research by (Kutluk and Gülmez 2014) also used Likert type statements.

(Sarrab, Al Shibli and Badursha 2016) also used survey questionnaires in his study on m-learning, and (Ali *et al.* 2015) used the questionnaire survey instrument in order to gain a perspective on the usability of the interfaces of m-learning applications for smartphones. (Huang *et al.* 2014) used a seven-point Likert scale to measure the level of agreement towards m-learning continuance intentions. (Almaiah and Jalil 2014) used questionnaires to investigate the perceptions of students towards m-learning. The study comprised demographic data and multiple choice questions on the usage of mobile devices with the use of a five-point Likert scale to explore the students' perceptions towards applying m-learning and another section based on the scales 1 to 3 intended to explore the students' expectations regarding m-learning services. (Hao, Dennen and Mei 2017) conducted an anonymous online survey. The survey instrument comprised a 30-item questionnaire developed from an extensive literature review, and then modified to fit the specific context of the study on m-learning acceptance. The objective of the research by (Hamidi and Chavoshi 2018) was also to assess student acceptance and compliance with m-learning. In order to collect data, questionnaires were used which were measured using the most common tool, the Likert scale (five-point) in order to assess students' attitude. (Ali and Arshad 2017) on the other hand collected descriptive statistics regarding students' perception towards the benefits and difficulties of m-learning measured using a five-point Likert scale.

2.5.2 Qualitative

Most qualitative research involves observation, and interviews with participants of a study. (Ekanayake and Wishart 2015) conducted qualitative research by observing and making field notes on a group of science teachers who were taught to develop learning material online with the use of cell phones for their technology acquainted students. These participants (teachers) felt that they were given only a very limited time to learn to use the device, as their inexperience was not taken into account. (Henderson and Yeow 2012) also conducted qualitative research, which showed that students felt it to be cost effective as it provided access to e-books, articles, and documents. It also provided note taking accessibility, fast internet access by means of emails, videos, sharing of information sites with other students, as well as being able to plan and organise their time, and prepare presentations and assignments with their iPads. However, they did find that some students could not afford iPads, and did not know how to fully use them.

(Archibald *et al.* 2014) conducted studies using qualitative data surveys by means of interviews using a content analysis approach of the quantitative data gained. The study by (Gikas and Grant 2013) collected data through student focus group interviews on stimulations and frustrations of mobile computing devices for student learning. The goal of the research was to provide thorough perspectives on students' experiences with applying mobile computing devices. The qualitative approach experiences of the respondents interviewed to share views. The primary method of data collection was focus group interviews, used to explore the perspective of the students. After contacting the course instructors, an invite through the email was sent to the course instructor's students. The focus group interviews used video chat, with the use of a Skype recorder. Krueger's (1994) strategy provided structure to the discussions, while focus groups are being interviewed. Semi-structured interview procedures were followed, which allowed for probing of different phrasing of the questions to all interviewees, as well as specific individuals.

2.5.3 Hybrid

The hybrid method used questionnaires, interviews, and observations on the participants of the study. An investigation was done by (Hargis *et al.* 2014) with the aim of finding out whether the implementation of the iPad has enhanced student-centred learning experience. It was found that both teachers and students tried their level best in making the implementation of iPads in the classroom a success. However, students needed to be encouraged and motivated to continuously make use of content available, as well as to ensure teachers aligned the curriculum followed in the class to the assessments given to students in the interactive applications. The method used was both quantitative (student) and qualitative (teacher). (Rossing *et al.* 2012) asked students to complete a survey after the final class session on the use of iPads for a learning activity which consisted of both Likert-scale and open-ended responses. Both qualitative and quantitative data was collected thus using a mixed method approach concurrently. The quantitative data was measured using the Likert-scale. The qualitative data aimed to gain an understanding of both opportunities and restrictions of various themes of mobile technology such as "access and availability of information, sharing and collaboration, novelty, learning styles and preferences, and convenience and functionality" (Rossing *et al.* 2012).

The data analysis of a study by (Heflin, Shewmaker and Nguyen 2017) used video footage in small-group interaction, a short written document from each group outlining the reasons for their decision on the discussion theme, and a questionnaire on students' perceptions and experiences. The qualitative method was useful in assessing the students' critical thinking concerning the discussion theme issued to students. The aim of the research was to determine whether having small discussion groups impacted on critical thinking. Unfortunately, the interpretation of certain behaviours could be easily misconstrued, as the video might not have contained audio. Finally, observation made it much easier to distinguish student engagement through speech, eye contact, gestures, and posture, than the use of technology. The quantitative survey provided questionnaires, allowing students to provide feedback on collaborative learning and mobile technology. (Donaldson 2011) used questionnaire surveys consisting of a section on demographic information, and questions on the intention of using m-learning. Interviews were used to gain an understanding of mobile devices for educating students, as well as on perceptions of internet communication for academic use.

2.6 Summary

Many m-learning studies have been conducted across the world. The studies have ranged from different perceptions of individuals including students and instructors, as well as on mobile applications for different subject content and the use of different mobile devices. Both instructors and students have indicated the benefits gained, as well as their concerns regarding m-learning. The quantity of m-learning studies on m-learning in higher education is increasing, however there are very few good quality studies providing evidence of effective m-learning (Kaliisa and Picard 2017). According to (Burton-Jones and Grange 2013), effective use means the use of a system that increases the user's goal of achievement. (Mutono and Dagada 2016) have stated that m-learning acceptance is still low in South Africa. It was highlighted that it would be important to know whether there can be acceptance of that which a student has no idea about. Whilst there is a wide use of mobile gadgets by the students, they know little about their benefits when used in education. According to (Iqbal and Bhatti 2017), it is of utmost importance to determine the factors affecting students' intentions to adopt m-learning as initiatives cannot be successful unless it is appreciated by students.

It is evident from the literature that there is no clear reason explicating the factors that influence the low adoption rate of smartphones for m-learning ensuring continuance intention by students' to use mobile technology to acquire new knowledge. (Hsiao, Chang and Tang 2016) state that user satisfaction and continuous usage has appeared as a dominant issue in the Information Systems literature. However, according to (Kaliisa and Picard 2017), large-scale studies assessing the effectiveness of m-learning remain inadequate, and the findings and conclusions of existing studies are debateable, as these lack a theoretical framework, especially within African higher education institutions. A study of the research on the measurement of use, acceptance and adoption of mobile technology, and introduced work carried out previously in these areas are provided in this chapter. Despite the large number of studies on m-learning, there still remains a gap in research as using smartphones for m-learning, however, its effective use is ofextreme importance, where a student's learning goals can be achieved. Therefore, the aim of this study is to fill the gap, as well as to provide answers, by exploring determinants that are most likely to influence the effective use of smartphones for m-learning in available research. This can only be achieved by its continuous use resulting from the satisfaction obtained over its use. The next chapter will explain the theoretical frameworks that have been used in previous research.

CHAPTER 3:

THEORETICAL FRAMEWORK

The following sections focus on the IS theories that have been used in perception studies. The theoretical frameworks used have been Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Expectation Confirmation Theory (ECT). Most of the research reviewed have used TAM (Technology Acceptance Model).

3.1 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) predicts a person's intention to participate in an action at a specific time and location. It proposes that the person's action is driven by behaviour intentions. Behaviour intentions has three determinants, which includes attitude toward a behaviour, subjective norms, and perceived behavioural control, as depicted in Figure 3.1 (Ajzen 1991).

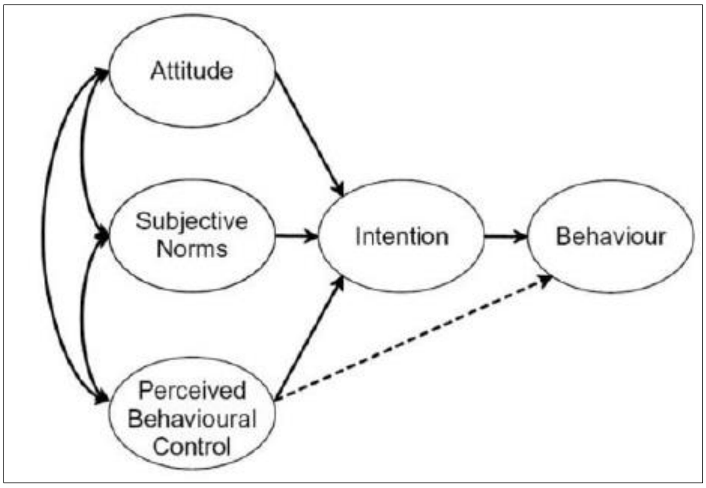

Figure 3. 1 - The Theory of Planned Behaviour (TPB) (Ajzen 1991)

3.1.1 Factors of TPB

The following are factors of TPB model:

a) *Behavioural Intention*: (Ajzen 1991) further posits that "intentions are indications of how hard people are willing to try, as well as of how much of an effort they are planning to exert, in order to perform the behaviour." Usually, the stronger the goal, the greater the possibility of the action been performed.

b) *Attitude* refers to the degree of feeling towards a task, which results in performing the action.
c) *Subjective Norm refers* to whether other important people think he or she should perform the action. It relates to a "person's awareness of the social environment surrounding an action".
d) *Perceived Behavioural Control* refers to an individual's feelings on performing a task which depends on specific circumstances (Ajzen 1991).

3.1.2 Strengths

According to (Mathieson 1991):

1. TPB does not assume that every context is the same. TPB's approach is that all participants make similar comparison. However, social factors in TPB may still show different changes in intention.
2. Control factors are independently used in TPB and recorded for each situation. (Ajzen 1985) differentiates between an individual's internal control factors comprising of skill and will power, and situation dependent external factors including time, opportunity, and the user's cooperation.
3. TPB provides more specific information by evaluating the system's performance on different outcomes, and identifying factors that participants feel might be barriers to the use of the system.

3.1.3 Limitation

The following are the limitations of using the TPB model:

1. TPB is more complicated to apply compared to TAM. This is due to the various user contexts applied by TPB. Other difficulties may arise if different users have different expectations of the same system. Certain TPB items may need to be as explicit as possible as the items may not apply to all users.

2. The stability of some of the control factors varies according to each situation (Ajzen 1985). A control factor will be fairly stable if the same skills acquired from the various situations, are required for different IS-related tasks (Mathieson 1991).

3. (Davis 1989) has stated that social issues are inadequately managed by TPB.

4. TPB is more costly to apply.

3.2 Technology Acceptance Model (TAM)

TAM predicts that a system's usage is directly affected by the factors "perceived ease of use, perceived usefulness and the attitude towards the use of the system" (Davis 1989). The relationship between the system features and possible use of the system is investigated with regard to perceived ease of use and perceived usefulness. A possible use of the system may indicate its success.

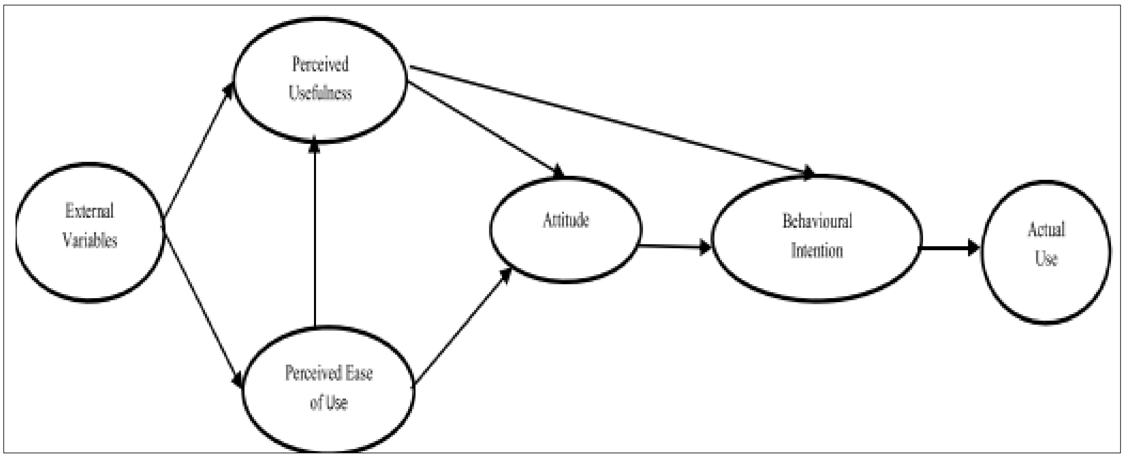

Figure 3. 2 – Technology Acceptance Model (TAM) (Davis, 1989)

3.2.1 Factors of TAM

Perceived usefulness and perceived ease of use are key determinants in the TAM model. Perceived usefulness refers to the extent to which a person relies on using a particular system to enable them to improve their performance in their job, whereas perceived ease of use refers to the effort required to use a system (Davis, 1989, p. 320). Perceived usefulness and perceived ease of use affect a users' attitude, which in turn influences intention to use and actual use of the system (Figure 3.2).

TAM2 is an extension of TAM (Venkatesh and Davis 2000) which reflects the impacts of “subjective norm”, “voluntariness” and “image”. The relationship among these three constructs shows whether a user will accept or reject of a system. It includes two moderators which are “experience” and “voluntariness”.

3.2.2 Strengths

As stated by Mathieson (1991), the following are strengths of the TAM model:

1. TAM is parsimonious and IT-specific.

2. Every situation evaluates TAM's factors in the same way, as the identification of a specific comparison of behaviour is not needed in TAM.

3. General information about the user’s perceptions of a system can be provided by TAM in a fast and affordable way.

3.2.3 Weaknesses

According to (Mathieson 1991), TAM accepts the factors usefulness and ease of use to be the key determinants for making decisions. There are three concerns which are:

1. The possibility of some situations having different factors to predict intention, except ease of use and usefulness, were not included within TAM, even though this may not be an essential part of the model.

2. Social factors are not clearly expressed in TAM, which are important if the variance can be recorded, especially if unexplained by other factors in the model.

3. Behavioural control is treated differently in the TAM and TPB models. Behavioural control includes expetise, prospects, and resources that are necessary to use the system which TPB takes into account. However, TAM includes ease of use (EOU), namely the user’s capabilities and skills needed by the system. Hence, the TAM model will miss certain important control issues.

3.3 C-TPB-TAM

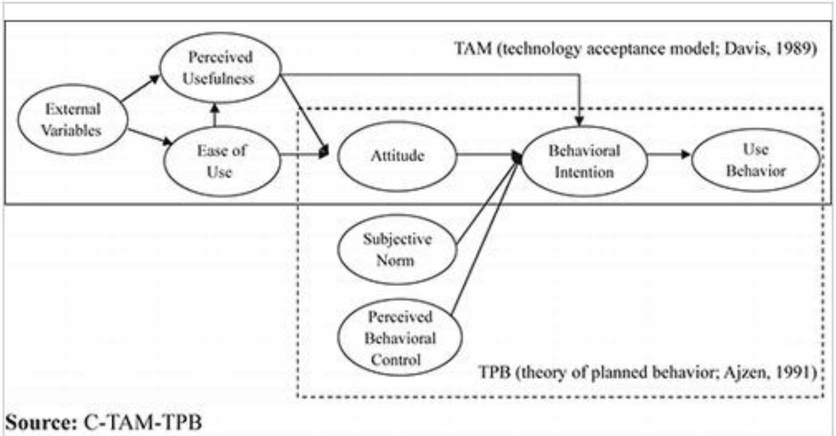

Figure 3. 3 – C-TAM-TPB

(Hsiao and Tang 2014) state that a hybrid model, TAM and TPB model are merged to form a hybrid model called C-TAM-TPB. This model combines the factors of TAM with the predictors of TPB. Personal control factors and social factors were excluded by (Davis 1989) in TAM (Figure 3.3). Therefore, these two important determinants of IT usage are included to provide a more comprehensive test.

3.4 Expectation Confirmation Model (ECM)

According to (Bhattacherjee 2001), Expectation-Confirmation Theory (ECT) posits that expectations, together with perceived performance lead to satisfaction, which is mediated through positive or negative disconfirmation between expectations and performance (Figure 3.4). It can be explained as one having an expection prior to any event. One is only satisfied if the belief is met positively, and one is dissatisfied if the belief results negatively. (Dağhan and Akkoyunlu 2016) has reported that the development of ECM by (Bhattacherjee 2001) has shown factors that are affected by the continuance usage intentions of users regarding information technologies. (Jiang and Klein 2009) have meanwhile stated that this makes ECT a powerful explanatory tool.

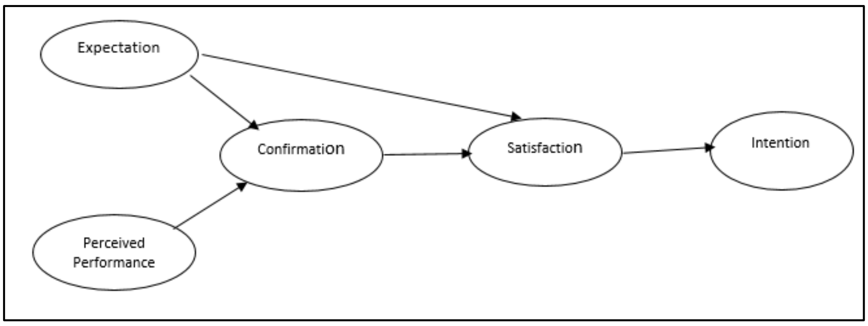

Figure 3. 4 – Expectation- Confirmation Model (ECM) (Bhattacherjee 2001)

3.4.1 Factors of ECM

According to (Bhattacherjee 2001), some of the factors that contribute to the model are as follows:

1. IS Continuance Intention: shows the intention of the users in respect of continuously using an information system which predicts the intention factor in the model.
2. Expectation: refers to the user's initial expectation of a specific technology before using it. It tries to understand the user's aim and gain by the use of the information system.
3. Satisfaction: refers to the user's feelings regarding previous use. (Bhattacherjee 2001), satisfaction is considered to be the central factor of Information System's Expectation Confirmation.
4. Confirmation: refers to the understanding with regard to expectations and the system's actual performance.
5. Perceived Performance: refers to the perception of actual performance.

3.5 Flow Theory

Flow theory is defined as (Csíkszentmihályi, 1990, p.4) "a state in which people are so involved in an activity that nothing else seems to matter; the experience is so enjoyable that people will continue to do it even at great cost, for the sheer sake of doing it." The complete concentration on a task involving a person's creative abilities, which leads to them being very confident, alert, strong and in control. A balance between the users' skills and challenges depicts the flow in an individual. Users are uninterested when their skillfulness is greater than the task given but nervous when the task is greater than their proficiency. When the user's level of competence and the activity is lower than the recommended value; users may feel indifference. Users experience excitement when both their skillfulness and the test exceeded the threshold values (Gao, Waechter and Bai 2015).

Flow theory consists of several dimensions, namely perceived enjoyment, concentration, perceived control, action and awareness, and curiosity. Perceived enjoyment exhibits the pleasure associated with completing the task, concentration reflects engagement with the task, whereas perceived control indicates the user's thoughts over the task and situation.

3.6 Will, Skill, Tool Model (WST)

The WST model was developed by (Knezek and Christensen 2008), to predict the combination of attitude, competence and access to technology as necessary mechanisms for effective incorporation of technology in an instructing and learning atmosphere.

The WST model factors are as follows (Agyei and Voogt 2011):

1. Will: Technology usefulness is influenced by the user's attitude towards computers.
2. Skill: It is user's ability to perform a particular task and option to take part in the activities.
3. Tools: It refers to the accessibility of technology tools.

3.7 Summary

Many theoretical frameworks have been used in m-learning studies. TPB has been included in a few studies on m-learning, as well as in numerous perception studies concerning health, products, services, and environment issues (Ghani et al. 2013; Hasan, Harun and Hock 2015; Ishii and Boyer 2016; Li et al. 2016; Maichum, Parichatnon and Peng 2016). The purpose of a study by (Cheon *et al.* 2012) was to identify and explore the factors in the adoption of m-learning and its association with each other. It used the TPB model to demonstrate whether the factors attitudes, subjective norms, and behavioural control affect m-learning adoption. Findings show that perceived behavioural control affects m-learning adoption, and therefore should be included in the model which is in accordance with TPB model by Ajzen (1985). Ignoring perceived behavioural control might not properly explain students' behaviour. According to (Mathieson 1991), TPB is a useful model but can be further developed. Sniehotta (2009) has reported that the theory does not account for intention-behaviour discrepancies, which is inadequate from an experimental and behaviour change perspective.

TAM is also a popular theory that explains the adoption of technology. The main advantages claimed for TAM are that it is parsimonious and IT specific (Mathieson 1991). The research by (Iqbal and Bhatti 2017) has explained and predicted the acceptance of IS by including the two main factors used in TAM. These factors affect the user's intention to use and the system's actual use. (Davis 1989) has suggested the inclusion of external factors in order to improve the predictive ability of TAM regarding future technology adoption could be improved by including external factors. Results were not totally consistent or clear when an analysis of experimental research using TAM was conducted, implying that significant factors were not included in the model (Mathieson 1991). (Hamidi and Chavoshi 2018) used TAM to predict adoption of technology by the main factors, but this failed to reveal the effects of user acceptance. Therefore context, trust, characters, and personal demands have been added to the existing TAM traditional model. Also, (Sarrab, Al Shibli and Badursha 2016) used TAM as a theoretical framework and not only found that perceived usefulness and perceived ease of use had a substantial positive effect on the user's adoption of m-learning systems, but that the factors ease of use, usefulness, enjoyment, suitability, as well as social and economic conditions also contributed considerably towards the adoption of m-learning. In a study by (Oluwatobi and Yemisi 2014), the TAM model as well as additional factors such as subjective norms, experience and motivation were included to determine the adoption of instructional technology by both instructors and students in an educational setting. It also assumed that the factors of perceived usefulness, ease of use and reliability of e-portal will determine a student's IT capability and demographic characteristics. The findings from a study by (Hao, Dennen and Mei 2017) show that students have a choice on their engagement in m-learning activities, which are influenced by a blend of educational, social, and personal creativity factors.

Both pedagogical and social factors may influence m-learning adoption, as personal innovativeness reveals a person's preference, and to an extent, is controlled by other people's actions. Other factors such as image, peer influence, and innovativeness does not only contribute to education, but also reveal social status, thereby demonstrating the complex perceptions of students towards m-learning. (Park, Nam and Cha 2012) have included factors such as self-efficacy, relevance for students' majors, system accessibility, subjective norm, perceived usefulness, perceived ease of use, attitude, and behavioural intention to use m-learning. The study results confirmed the acceptability of the model to explain students' acceptance of m-learning. Attitude was the most important factor in explaining the causal process in the model, followed by students' majors and subjective norms. (Venkatesh *et al.* 2003) has reported that social influence is included as a factor affecting behavioural intention in other acceptance models, as well such as TAM and TPB. The adoption of a new technology by indirectly influencing their attitude through perceived usefulness and perceived ease of use could encourage people by the factor social influence. A study by (Mtega *et al.* 2012) on the use of mobile phones showed differing usage, such as text messages, calls, or use of some advanced educational applications. However, certain users failed to utilise these resources, as they were incapable of accessing them, or they did not have capable devices that supported the resources.

(Mathieson 1991) noted that TAM is much more straightforward to use than is TPB. A standard instrument was developed for TAM, while a different instrument had to be developed in TPB for each of the different context. Furthermore, validated scales and availability of strong empirical support make it suitable for investigating Information technology (IT) adoption. TAM's weakness is its inability to clearly state its external factors. A Unified Theory of Acceptance and Use of Technology (UTAUT) model was adopted by (Mutono and Dagada 2016) by means of which to determine the factors that influence the students' intention to use and to analyse the student's acceptance of m-learning, and as well to assess the factors that have a significant relationship with behaviour intention to use m-learning, post school education, and training environments. The study findings indicated that there is a positive attitude to behavioural intention to use m-learning which could be due to the use of mobile gadgets among the students.

A dissertation by (Donaldson 2011) reported that the factors performance expectancy, social influence, facilitating conditions, as well as perceived playfulness, positively predicted learning by use of mobile devices. However, findings also showed that the degree of voluntary use negatively predicted the intention to use mobile devices for learning. According to (Mathieson 1991), both TPB and TAM could be used together very effectively. (Tavallaee, Shokouhyar and Samadi 2017) examine the factors of m-learning acceptance by students at the universities in Tehran, based on C-TAM-TPB model, which combines TPB and TAM. It was discovered that PBC and behavioural intention do have an effect on the students' actual behaviour with regard to the acceptance of mobile learning, where students reach the behavioural intention stage when their attitude towards using the device is positive. The factors usefulness and ease of use have influenced students' attitudes towards acceptance of m-learning. (Mathieson 1991) also stated that although TAM surpassed TPB, both models provided good predictions on IS use. TAM is easier and cheaper to use, while TPB provides more information about the factors users consider when making their choices. Detailed information on a particular group can be provided by TPB. Based on the results of TAM's general and inexpensive information, only affected areas could use the more specific and expensive information that is required by TPB.

A study by (Koo, Chung and Kim 2015) adopted the IS continuance model by (Bhattacherjee 2001), but added the factor user competence, however, it was found that the results were inconsistent with the findings of (Bhattacherjee 2001), as satisfaction remained unsupported. Furthermore, perceived ease of use only affected exploitative use. A study by (Hsiao, Chang and Tang 2016) also used ECM to provide some understanding relating to a user's social background and continuance intention of social apps. The results reveal that factors satisfaction, perceived enjoyment, habitual use, and social ties has a substantial influence on the users' continuance intention of of utilising social apps which demonstrates similarity with the findings of the IS continuance model (Bhattacherjee

2001). This confirms the most influential factor in explaining users' continuance of using social apps to be satisfaction. Findings by (Bhattacherjee 2001) shows that user satisfaction with previous use has a relatively stronger effect on the dependent factor, even though the perception of post-acceptance usefulness continues to influence users' continuance intention. User satisfaction is determined mainly by users' confirmation of expectation from previous use, and then by perceived usefulness. Furthermore, confirmation also has a significant influence on the post-acceptance of perceived usefulness. (Kim, Lee and Rha 2017) conducted a study using the Innovation Diffusion Theory (IDT) and Model of Innovation Resistance (MIR), which showed this to be an important contributor in increasing the intention, but also reducing the struggle of using m-learning. Though, (Agyei and Voogt 2011) highlighted that technology integration in the classroom was a strong predictor of skill.

3.8 Conclusion

According to (Mathieson 1991) the information results provided during the improvement and post-implementation evaluation by TPB is probably more useful than TAM. TPB focuses its development efforts on specific problems. TAM identifies the problem, but would not provide reasons for the existence of the problem or issue. Although there will be questions regarding the validity of the TPB's approach to social pressures, the information could be valuable if it identifies possible sources of resistance. TPB may provide more specific information into the reasons a user might be dissatisfied. (Legris, Ingham and Collerette 2003) concluded that the TAM model ought to incorporate human, social change, and innovation processes even though it has been found to be a useful model. The TAM original version consisted of the factors perceived usefulness (PU), perceived ease of use (PEOU), attitude (AT), behaviour intention (BI), and actual use (U). Based on these five factors, ten associations have been examined. They are PEOU with PU, PU with AT, PEOU with AT, PU with BI, PEOU with BI, AT with BI, AT with U, BI with U, PEOU with U, and finally PU with U.

All relations have had high proportions of positive results, with some inconsistencies. Although there are positive results relating to IT adoption, this is not adequate to predict adoption in IT. The new version of Davis's model, called TAM2, has an additional factor, called subjective norms. However, in the Theory of Planned Behavior (TPB), the effect of subjective norm is included and acknowledged.

According to the study by (Mtebe and Raisamo 2014), students believe that they can be easily influenced to accept and use m-learning by their classmates and friends. (Bhattacherjee 2001) stated that understanding continuance use is the goal of ECM. However, studies view continuance use as an extension of acceptance behaviours, as they employ the same set of pre-acceptance factors which are used to explain both acceptance and continuance decisions. An important first step toward realising IS success is the initial acceptance of an IS, but extended feasibility and ultimate achievement of an IS depends on its continued use, instead of an introduction to its use.

This chapter provided a foundation for this research study by presenting an overview of the various IS frameworks and theories that have been developed, and has also demonstrated the various works in which they have been measured. It has presented an overview of the benefits and limitations of using each. Analysing and comparing these tools and their factors has revealed that research lacks attention to measuring the factors influencing the continuous and constructive use of mobile technology which is important to its sustainability. The next chapter explains the methodology that was followed in order to reach the objectives of this research, by reviewing a number of frameworks organised to investigate factors that influence students in effectively using smartphones for m-learning.

CHAPTER 4:

METHODOLOGY

Chapter Four presents the research methodology used in this study. It addresses the data collection, the target population, sampling techniques, size and validity of the instrument, method of analysis, reliability and validity approaches, the model fit, determination of the coefficient, the strength of the relationship between factors, as well as the model's predictive validity tests to be used in the study. The research proposes to identify those factors that are likely to influence students in the effective use of smartphones for m-learning. The study is descriptive in nature. The research will employ a questionnaire to gather data, and thereafter make use of suitable statistical techniques to evaluate the data and reach deductions.

4.1 Data Collection

An instrument is a tool for evaluating, noting, or recording quantitative data. The instrument may be a test, questionnaire, tally sheet, log, observational checklist, inventory, or assessment instrument that must be identified before the researcher collects data (Creswell 2014). The instrument to be used in the analysis of this study is a questionnaire survey that will be administered to interested participants (Refer Appendix A). The questionnaire contains two parts. Part 1 of the questionnaire contains general information to collect data on demographic information and general m-learning questions. Part 2 contains multiple choice questions to explore student perceptions consisting of 64 items (three to seven items for each of the thirteen factors), adapted from the previous studies (see Table 4.1). It was a combination of TAM, ECM, TPB, Flow, and WST factors that were used in prior research. The questions for the factors (intention to use, expectation, confirmation, satisfaction, attitude, subjective norm, perceived behavioural control, perceived usefulness, perceived ease of use, perceived reliability, concentration, skill and effectiveness) were adapted from articles (Refer to Table 4.1). The questions were provided on the ground of comments from researchers in the field of information systems, e-learning and m-learning, who had developed the existing models or used the models in their research. The survey consisted of a Semantic Differential Scale to measure participants' perceptions with a seven-point Likert scale from 1 to 7. All questions consisted of anchors at each end of the seven-point Likert scale. The response anchors ranged from 'totally disagree' to 'totally agree'.

Table 4. 1 - Factors influencing the use of smartphones for m-learning

Factor	Item	Measurement	Adapted from Source
Intention to Use	ITU01	I intend to use smartphones for m-learning on a regular basis in the future.	**(Bhattacherjee 2001)**
	ITU02	I plan to use smartphone for m-learning in the future.	
	ITU03	I prefer to use smartphone for m-learning in the future.	
	ITU04	I like to use smartphone for m-learning in the future.	
	ITU05	I will strongly recommend that others use smartphones for m-learning.	
Expectation	EXP01	If I use smartphones for m-learning, I will increase my effectiveness on the task.	**(Bhattacherjee 2001)**
	EXP02	If I use smartphones for m-learning, I will gather complete and timely information.	
	EXP03	If I use smartphones for m-learning, my peers will perceive me as competent.	
	EXP04	If I use smartphones for m-learning, I will increase my sense of accomplishment.	
Confirmation	CONF01	My experience with using smartphones for m-learning was better that what I expected.	**(Bhattacherjee 2001)**
	CONF02	The service provided by the m-learning system for using smartphones was better than I expected.	
	CONF03	Overall, most of my expectations from using smartphones for m-learning were confirmed	
Attitude	ATT01	Using smartphones for m-learning allows me to get my work done more quickly.	**(Davis 1989)**
	ATT02	Using smartphones for m-learning helps me gain a better understanding of the content of my courses.	**(Ajzen 1991)**
	ATT03	Using smartphones for m-learning helps me to do well and get high marks in my courses.	
	ATT04	Using smartphones for m-learning helps me to interact with the instructor and other students in class.	
	ATT05	Using smartphones for m-learning is a good idea.	
	ATT06	It is a good idea to apply m-learning using smartphones.	
	ATT07	It is fun to work with m-learning using smartphones.	
Subjective Norm	SN01	Most people who are important to me think that it would be a good idea to use smartphones for m-learning.	**(Davis 1989)**
	SN02	My instructors think that I need to regularly use smartphones for m-learning.	**(Ajzen 1991)**
	SN03	My class colleagues think that I need to regularly use smartphones for m-learning.	
	SN04	My close friends think that I need to regularly use smartphones for m-learning.	
	SN05	My university encourages me to regularly use smartphones for m-learning.	
Perceived behaviour control	PBC01	I have what it takes to use smartphone for m-learning.	**(Ajzen 1991)**
	PBC02	I have sufficient data bundles available while using my smartphone for m-learning.	
	PBC03	I can afford the device and data costs.	
	PBC04	I am entirely in control of using my smartphone for m-learning.	
Perceived usefulness	PU01	Using smartphones for m-learning helps me achieve learning success.	**(Davis 1989)**
	PU02	Using smartphones for m-learning promotes good learning practices.	
	PU03	Using smartphones for m-learning improves my performance academically.	
	PU04	Using smartphones for m-learning allows me to get my work done more quickly.	
	PU05	Using smartphones for m-learning enables me to get information anywhere at any time.	
	PU06	Using smartphones for m-learning helps me collaborate instantly with colleagues about anything I am not sure about.	
Skill	SK01	I am able to perform the most difficult of tasks on the smartphone for m-learning.	**(Agyei and Voogt 2011)**
	SK02	I have found easier ways to complete and access the tasks on the smartphone for m-learning.	
	SK03	I am motivated to perform well by using the smartphone for m-learning.	
	SK04	I explore new uses of the smartphone to support my task for m-learning.	
	SK05	I often experiment with new ways of using the smartphone to accomplish my tasks on m-learning.	
	SK06	I often find new uses of the smartphone in performing my task for m-learning.	
	SK07	I use the smartphone in novel ways to complete my tasks for m-learning.	
Perceived ease of use	PEOU01	It is easy to use smartphones for m-learning.	**(Davis 1989)**
	PEOU02	It is simple to use smartphones for m-learning.	
	PEOU03	It is convenient to smartphones for m-learning.	
	PEOU04	It is easy to use smartphones to access information in m-learning.	
	PEOU05	Using smartphones for m-learning is user-friendly.	
Concentration	CON01	When using my smartphone for m-learning I forget about the people around me.	**(Lee 2010)**
	CON02	When using my smartphone for m-learning I am not unaware of my surroundings.	
	CON03	When using my smartphone for m-learning I forget about my time.	
	CON04	I am not distracted by other social software application on my smartphone while m-learning.	
Satisfaction	SAT01	I am satisfied with effectively using smartphones for m-learning.	**(Bhattacherjee 2001)**
	SAT02	I am satisfied with using smartphones for m-learning.	
	SAT03	I am pleased with the experience of using smartphones for m-learning.	
	SAT04	I am contented with using smartphones for m-learning.	
	SAT05	I am delighted with using smartphones for m-learning.	
	SAT06	I feel very confident with using smartphone for m-learning.	
Effective Use	EU01	Using smartphone for m-learning has changed my learning habit.	**(Burton-Jones and Grange 2012)**
	EU02	Using smartphone for m-learning has improved my academic performance.	**(Burton-Jones and Grange 2013)**
	EU03	Using smartphone for m-learning has improved my ability to engage.	
	EU04	Using smartphone for m-learning has improved my ability in accomplishing my tasks.	
	EU05	Using smartphone for m-learning has allowed me to accomplish my tasks in much more exciting and interesting ways.	
	EU06	Using smartphone for m-learning has allowed me to accomplish more tasks in less time.	
	EU07	Using smartphone for m-learning has made me more creative and innovative in my learning.	
Continuous Intention	CI01	I will use smartphones for m-learning on a regular basis in the future.	**(Iqbal and Bhatti 2017)**
	CI02	I will frequently use smartphone for m-learning in the future.	
	CI03	I will strongly recommend that others use smartphones for m-learning.	

4.2 Target Population

A group of individuals that a researcher can identify and study as having some common and defining characteristics is known as a target population (Creswell 2014). A hardcopy of this questionnaire was distributed to the students belonging to the Department of Information Technology (IT) at the Durban University of Technology (DUT). Students were notified at the beginning of the survey, by means of a consent form, of their voluntary participation, and their responses private and confidential. Students were also advised that they could remove themselves from participation at any time. Data collected in this research will be used for this purpose only. The sample size was 569 students.

4.3 Data Processed

A systematic sampling method was used. A quantitative sampling procedure, in which the researcher chooses samples at static periodic intervals until the preferred sample size is accomplished, is known as systematic sampling (Creswell 2014). It is a type of probability sampling method with a random starting point, and a fixed periodic interval, that will ensure an equal opportunity for every student of being selected from the population list. The researcher contacted the respective lecturers to set up a time and date for the questionnaires to be administered. There were difficulties in getting the third level students to participate in the survey as attendance was low. These third year students comprised approximately 250 students. Some third year students provided the researcher with a time during which these students will be available, and thus the questionnaire was administered to these students during the time the students were available. It can therefore be said that word-of-mouth also assisted the researcher in conducting the survey and increasing the number of respondents. The survey took at least one month to complete. On the completion of the data collection in this study and after the researcher knew that further attempts at surveying IT students not yet covered in the survey would be fruitless, the researcher began examining the raw data. Missing data and outliers were some of the data abnormalities that was examined. All incomplete questionnaires were excluded from the study. A total of six incomplete surveys was found, and subsequently removed from the total of 575 questionnaires. Once data collection and examination had been concluded, the data was then captured in an Excel spreadsheet, and saved as a .csv file so that it could be made ready for analysis.

Table 4. 2** - **Demographic profiles of respondents

Characteristics	Category	Frequency	Percentage
Age	17	7	1,23
	18	71	12,48
	19	107	18,80
	20	143	25,13
	21	103	18,10
	22	72	12,65
	23	33	5,80
	24	12	2,11
	25	7	1,23
	>25	14	2,46
Gender	Male	363	64
	Female	206	36
Location	Urban	398	69,95
	Rural	98	17,22
	Semi-Rural	73	12,83
Study Level	First Year	268	47,10
	Second Year	233	40,95
	Third Year	64	11,25
	Fourth Year	4	0,70
Device Ownership	smart phone	569	100,00
	iPad	37	6,50
	tablet	146	25,66
	iPod	14	2,46
	PDA	4	0,70
Use of Smartphone	Study	101	17,75
	Entertain	109	19,16
	Study and Entertainment	359	63,09
Length Use	Not used	52	9,14
	1 - 4 weeks	21	3,69
	1 - 3 months	29	5,10
	4 - 6 months	53	9,31
	7 - 11 months	62	10,90
	1 - 3 years	157	27,59
	> 3 years	195	34,27
Internet Contract	Yes	190	33,39
	No	379	66,61

4.3.1 Demographic Profiles of Respondents

Information captured on the respondent's demographic profile, included the respondent's age, gender, location at which respondent resided, respondent's level of study, type of mobile device owned by respondent, use of smartphone, duration of time spent on using m-learning as well as subscription to an internet contract was obtained from the first section of the questionnaire survey

(Table 4.2). An analysis of demographic data obtained shows that the largest percentage of respondents on the survey were aged 20 (25.13%), followed by respondents aged 19 (18.8%), 21 (18.1%), 22 (12.65%), 18 (12.48%), 23 (5.8%), 24 (12.65%), both 17 and 25 years (1.23%), as well as respondents more than 25 years (2%). The largest percentage of respondents were male (64%) than female (36%). A majority of the students can be currently located in urban areas (69.95%), as opposed to rural (17.22%) and semi-rural (12.83%) areas. Most of the respondents were in their first year of study (47.10%), followed by second year students (40.95%), third years (11.25%) and fourth years (0.70%). In addition to owning smartphones, a large number of the respondent also owned tablets (25.66%), iPads (6.50%), iPods (2.46%) and PDA's (0.70%). A large percentage of the students used their smartphones for both study and entertainment purposes compared to respondents only using it for study (17.75%) and entertainment (19.16%) purposes. Most of the respondents did not have any internet contract (66.61%) compared to those respondents having subscribed for one (33.39%).

4.4 Data Analysis

The analysis of two conceptually different models, namely the measurement model and the structural model, are emphasised in data analysis, which consists of a two-step model-building approach proposed by Anderson and Gerbing (1988). The measurement model specifies the association among the observed factors underlying the factors. The structural model specifies the association among the factors as suggested by the theory (Schumacker and Lomax 2010). The measurement model focuses on evaluation of the psychometric properties of reliability, convergent validity, and discriminant validity. The reliability, convergent validity, and discriminate validity are assessed. (Hair *et al.* 2012) have stated that the measures of convergent and discriminant validity demonstrates the strength of the measurement model. Moreover, the measurement instrument was well constructed to remove ambiguity that may confuse respondents. The factors from TPB, TAM, ECM, Flow and WST theoretical frameworks were used as the identified factors influencing the effective use of smartphones for m-learning. The TPB showed that actual behaviour is considered by the factors attitude, subjective norm and behavioural control (Ajzen 1985). According to the prediction of TAM, a system's use is directly influenced by perceived ease of use, perceived usefulness and attitude towards using the system (Davis 1989). According to (Bhattacherjee 2001), the ECM of IT continuance is based on the users' continuous intention to use dependent on their satisfaction with the Information System (IS). The Flow theory describes the state whereby users forget about the surrounding environment (Lee 2010). The WST model was developed by (Knezek and Christensen 2008), predicting the level of expertise incorporated as a function of attitude, competence and access to technology.

Hence, this study proposes to use the TPB, TAM, ECM, Flow and WST theories to enable the researcher to identify as many possible factors that influences student perceptions on the effective use of smartphones for m-learning. This study will use the following factors: expectation, satisfaction, confirmation, perceived usefulness, perceived ease of use, skill, attitude, subjective norm, perceived behaviour control, intention to use, concentration, and effective use, as shown in Table 4.1. These identified factors were then used to test sample data for reliability, validity and relationships. Exploratory and confirmatory factor analysis were conducted to investigate the relationships among observed sets of factors.

4.4.1 Data Exploration using Factor Analysis

According to (Costello and Osborne 2005), Exploratory Factor Analysis (EFA) reduces large number of factors. It also examines the structure or relationship between factors. (Yong and Pearce 2013) suggested the use of EFA to discover patterns in a set of factors to simplify interrelated measures. EFA is used to find the number of factors influencing other factors, and to analyse which factors are common.

4.4.2 Data Exploration using Principal Component Analysis

Principle Component Analysis (PCA) is a default process of extraction and is only used for data reduction. The aim of the analysis is to include as many factors as possible in the analysis. It is simply used to reduce the interrelated observed factors to a smaller set of essential independent combined factors. The number of observed factors is reduced by PCA to a smaller number of factors, which explains most of the variance of the observed factors.

4.4.3 Model Developed Using Structural Equation Modelling

Structural Equation Modelling (SEM) depicts the association among observed factors, with the simple goal of providing a quantitative test of theoretical models hypothesised by using different types of models. SEM analysis is determined by the SEM exploration which shows the extent to which the theoretical model is supported by sample data. If the sample data supports the theoretical model then more complicated theoretical models can also be hypothesised. The popularity of SEM has many reasons. Firstly, SEM techniques are preferred quantitively as it allows for complex theoretical models to be modelled and tested according to statistics. Secondly, SEM techniques clearly takes measurement errors into account when data is analysed according to statistics to include unnoticed and observed factors, and measurement inaccuracies in some SEM models. Thirdly, more advanced theoretical SEM models can be analysed effortlessly by means of SEM. And, finally, software programs used by SEM have become increasingly user-friendly (Schumacker and Lomax 2010).

This study utilised SEM to analyse the data, in view of the fact that it has a powerful statistical technique of measuring and evaluating cause and effect of relationships at the same time for theoretical models (Schumacker and Lomax 2010). SEM has become the most accepted multivariate technique to analyse causal relationships among factors especially in science, social science as well as social psychology (Kalema, Olugbara and Kekwaletswe 2011; Adegbenro and Olugbara 2018; Joseph and Olugbara 2018). SEM has been used to analyse student priorities in using course management systems (Kalema, Olugbara and Kekwaletswe 2011), investigate computer application technology in ICT enhanced classrooms (Adegbenro and Olugbara 2018), as well as evaluate municipal e-government readiness (Joseph and Olugbara 2018). Confirmatory Factor Analysis (CFA) will be used to test the theoretical model that will be developed based on the important factors identified by EFA in order to study relationships among those factors identified as well as its fit model. The SEM technique will be used as it provides more recognition to the validity and reliability of observed scores from measurement instruments. SEM does not separate, but explicitly takes measurement error into account when statistically analysing data, at the same time able to analyse more advanced SEM models.

4.4.3.1 Reliability and Validity

Reliability is used for the purpose of estimating the consistency of an individual's response to items being measured (Shin 2009). The estimate of internal consistency, which refers to the degree to which responses are consistent across the items within a scale, measured the reliability. The internal consistency will be used to test by Cronbach's Alpha for the effective use of smartphones for m-learning using the abovementioned existing model. The Cronbach's alpha applies a criteria whereby the acceptable value must be greater than 0.70, and is computed as follows:

$$\alpha = \frac{N.\bar{c}}{\bar{v}+(N-1).\bar{c}} \qquad (4.1)$$

Reliability of questions, composite reliability of factors, and variance removed by factors normally assesses the convergent validity (Fornell and Larcker 1981). Further to Cronbach's Alpha, composite reliability was also used to determine the reliability and validity of the models. Due to the Cronbach's alpha overestimating or underestimating scale reliability, Composite Reliability (CR) is the preferred method as it may lead to higher estimates of more accurate reliability. It measures the reliability of the indicators where the values are between 0 and 1. CR values greater than 0.7 provide adequate consistency (Gefen, Straub and Boudreau 2000). An associations between an item and factor is represented by an estimation of the CR, according to suggestions by Henseler et al. (2009) as follows:

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \left(\sum_{c=1}^{n} \delta_i\right)} \tag{4. 2}$$

Convergent validity can also be assessed using Average Variance Extracted (AVE), which is comparable to the proportion of the variance explained in factor analysis. Convergent and divergent validity are both tested by *AVE.* The values are between 0 and 1 and AVE should exceed 0.5 (Fornell and Larcker 1981; Bagozzi and Yi 1988). The amount of change that a factor records from its evaluation of items is determined by the Average Variance Estimate (AVE) and is calculated as follows (Henseler et al. 2009):

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^{\,2}}{\sum_{i=1}^{k} \lambda_i^{\,2} + \sum_{i=1}^{k} Var\ (e_i)} \tag{4. 3 }$$

The degree to which a particular factor is different from other factors is indicated by discriminate validity (Suki 2011). To establish discriminant validity, it should be demonstrated that the factors that are actually unrelated share no relationship at all. An alternative method of estimating discriminant validity for reflective models is the cross-loadings criterion. At a minimum, no indicator factor should have a higher correlation with another factor than with its own factor. If it does, the model is inaccurately specified. The Fornell-Larcker criterion establishes discriminant validity by the use of AVE. The minimum criteria for each factor is that the square root of the AVE value should be higher than its correlation with any other factor. This means that for any factor, the variance shared with its section of indicators is more than the variance it shares with any other factor. As stated by (Fornell and Larcker 1981), associations among each of the questions in the survey can be assessed by applying discriminant validity as well as the variances and covariance between the factors (Igbaria et al. 1994).

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 (y_i - \bar{y})^2}} \tag{4. 4}$$

The mean is the average of all scores, which is computed by dividing the total of the scores by the total number of scores (Creswell 2014).

$$\bar{x} = \left(\sum x_i\right)/n \tag{4. 5}$$

The standard deviation (SD) shows the average difference between each individual score and the mean.

$$s = sqrt\left[\ \sum (x_i - \bar{x})^2 \,/ (n-1)\right] \tag{4. 6}$$

Factor loadings indicates an association between factors and observed factors. Factor loadings offers information about the extent to which a certain observed factor is able to measure the factor. The factor loading is referred to as validity coefficients as the multiplication of the factor loading by the observed factor score specifies whether the amount of the observed factor score variance is valid (Schumacker and Lomax 2010). It shows inter-correlations between factors, and loads onto specific factors. The factor loading must be greater than 0.7, which shows the power of the relation.

Multi-collinearity exists when two or more independent factors are highly inter-correlated which may lead to inflated standard errors, result in significance tests of independent factors unreliable, and prevents assessing the relative significance of one independent factor when compared to another. When the variance inflation factor (VIF) coefficient is higher than 4.0, then a common rule is that multi-collinearity may exist. Model fit determines the degree to which the sample variance-covariance data fit the structural equation model. Different fit indices are used to test the new model developed. A combination of different model-fit criterias to assess the fit of the model contrasts between models and the model simplicity are recommended (Hair et al. 1992). Common model fit measures used to assess the model's overall goodness of fit are the Standardised Root Mean Square Residual (SRMR) and Normalised Fit Index (NFI). The square root of the difference between the remainder of the selected covariance matrix and the assumed covariance model is called SRMR. There is a difference between observed correlation and projected correlation. Values for the SRMR range from 0 to 1.0, however a value exceeding 0.08 are deemed acceptable (Hu and Bentler 1999).

$$SRMR = \sqrt{\frac{\sum_{i=1}^{P}\sum_{j=1}^{i}\left[(s_{\ddot{y}} - \hat{\sigma}_{\ddot{y}})/(s_{ii}s_{jj})\right]^2}{p(p+1)/2}} \tag{4. 7 }$$

A comparison between the X^2 value of the model to the X^2 of the null model is estimated by the NFI. The suggested cutoff criteria should be NFI >= 0.95, and a value between 0.90 and 0.95 is considered to be marginal, values above 0.95 is good, but a value below 0.90 is considered to be a poor fitting model. NFI is computed as follows:

$$NFI = \ (X_{null}^2 - x_{model}^2)/x_{null}^2 \tag{4. 8}$$

R-square or R^2, also referred to as the coefficient of determination, is a general measurement of the effect size of the structural model. The hypothesised contributing paths were estimated to test the structural relationship. The R^2 of each dependent factor indicates the appropriateness of the data to the model. The amount of variance in the dependent factor is shown by R^2, and is computed as follows (Cornell and Berger 1987):

$$R^2 = 1 - \frac{\sum(y_i - \bar{y})^2}{\sum(y_i - \bar{y})^2} \tag{4. 9}$$

Effect size is a statistical concept that measures the strength of the relationship between factors on a numeric scale. F^2 is used to calculate the contribution of the amount of variance each exogenous factor contribute to the endogenous factor. This is derived by calculating the R^2 values for independent factors, when each factor is excluded ($R^2_{excluded}$) and included ($R^2_{included}$) to test for its significance. The effect size f^2 is computed as follows (Helm et al. 2010):

$$F^2 = \left(R^2_{included} - R^2_{excluded}\right) / \left(1 - R^2_{included}\right) \tag{4.10}$$

Predictive relevance (Q^2) is significant to assess the predictive validity of complicated models (Akter, D'Ambra and Ray 2011). It refers to “a synthesis of cross validation and function fitting with the perspective that the prediction of observables is of much greater relevance than the estimation of what are often artificial factor – parameters” (cf. Chin 2010, p. 679; Geisser 1975, p. 320). Thus, Q^2 shows whether the data collected empirically can be remodelled with the help of the model and the PLS constraints (Fornell & Cha 1994). To identify that the item values were well reconstructed, the Q^2 values more than zero were tested for predictive relevance and is computed as follows:

$$Q^2 = \left(Q^2_{included} - Q^2_{excluded}\right) / \left(1 - Q^2_{included}\right) \tag{4. 101}$$

4.5 Conclusion

Chapter 4 discussed the data collection procedures and instruments, target population of the study and the research methodology used in this study. It discussed how the collection of data was analysed, reviewed the research design of the study and the research methods used. This chapter also evaluated the study’s research methodology and the measurements to be computed in the study. A thorough analysis of the results of this study will be conducted in the next chapter as well as an explanation of the findings.

CHAPTER 5:

DATA ANALYSIS AND RESULTS

This chapter provides the findings from the self-administered questionnaire (refer to Appendix A) used to survey the perceptions of the Information Technology (IT) students from the Department of Information Technology at the Durban University of Technology (DUT) on the effective use of smartphones for m-learning, as well as the data analysis results of the developed framework on effectively using smartphones for m-learning by applying the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach. PLS-SEM results of both the measurement and structured model are presented to determine the interdependencies or relationships between factors impacting on the effective use of m-learning and to test and validate the effectiveness of smartphones for learning at any place. The factors intention to use, expectation, confirmation, satisfaction, attitude, subjective norm, perceived behavioural control, perceived usefulness, perceived ease of use, perceived reliability, concentration, skill and effectiveness; taken from the theories (TPB, TAM, ECM, Flow, and WST) were evaluated for any relationships or interdependencies. A new model was developed to predict the effective utilization of smartphones for m-learning (Questions 2 and 3).

5.1 Relationships Between Identified Factors Influencing the Effective Use of Smartphones for M-Learning

The research data was analysed according to the path analysis method using the Smart PLS 3.0 software, a Partial Least Square Structural Equation Modelling software application used to determine any interdependencies or relationships between identified factors influencing the effective use of smartphones for m-learning. An analysis to investigate the predictive power of the TPB factors, the prediction on the adoption of the TAM factors, the prediction on the continuous use of the ECM factors, the prediction of the student's mental state of absorption with regards to factors associated with the Flow theory, including relationships between the WST factors that influence the proper use of smartphones for m-learning was conducted. The sample data underwent input and the measurement and structural model analysed. The measurement model was assessed for reliability (Refer Chapter 4 – Equations 4.1 and 4.2), as well as convergent (Refer Chapter 4 – Equation 4.3), and discriminant validity (Refer Chapter 4 – Equation 4.4). The structural model was assessed for multi-collinearity, determination of the coefficient, model fit, the path of the coefficient size and significance, effect size and predictive relevance (Refer Chapter 4 – Equation 4.5 to 4.11) were used to explain the hypothesis.

The PLS software was used to estimate the path of the coefficient size, significance, and effect size by means of a bootstrapping procedure with 1000 sub-samples. In order to evaluate the predictive relevance of all factors, a blindfolding procedure was conducted. The measurement of the TPB, TAM, ECM, Flow, and WST models has led to building two possible models, namely the intention to use (ITU) and continuous use (CU) models. The results show that the CU model shows possibilities for further development. After using different factors, satisfaction and continuous intention were chosen as predictors of effective use. A new model was developed for the effective use of smartphones for m-learning and tested for reliability and validity, model fit, effect size as well as the model's predictive relevance.

5.2 Measurement Model - Reliability and Validity

The measurement model identifies the association among observed factors underlying the unobserved factors whereby an assessment of the reliability and validity of a model is done. Cronbach's Alpha and composite reliability (Henseler et al. 2009) test the reliability of a model whilst convergent and discriminant validity (Fornell and Larcker 1981) tests the validity of a model.

5.2.1 Indicator Reliability

The indicator reliability checks whether an item is a good measurement of the latent factor. Item loadings greater than the value 0.5 indicate indicator reliability, as stated by Hulland (1999). The Outer Model Loadings, were assessed for all models. Table 5.1 shows that the lowest item value for the TPB model was 0.537 (PBC03) and highest item value 0.894 (ITU04) and the minimum item value was 0.642 for ATT04 and the highest value being 0.910 for PEOU02 for the TAM model (Table 5.2), whereas in the ECM model (Table 5.3), the minimum item value has been 0.748 for EXP03 and maximum being 0.951 for CON02. The Flow model, as shown in Table 5.4, consisted of the least loading of 0.523 for the item value PBC03 and the highest was for the item indicator loading CON01 (0.899), and the WST model (Table 5.5) had the lowest item indicator loading of 0.523 for PBC03 and IT04 had the highest value of 0.895. With the use of the TPB and TAM models, the first possible model, the ITU model, was developed (Table 5.6), which shows that the least item indicator loading value is 0.779 for EU01 and the highest being for ITU04 (0.894). With the use of the ECM model, the second possible model, the CU model (Table 5.7) was developed, which shows that the values ranged from a low of 0.777 for EU01 and the highest being 0.951 for CI02. As the second possible model seems more promising, this resulted in the Newly Developed Model, as shown in Table 5.8, which had the lowest item indicator loading value of 0.778 (EU01) and highest value of 0.951 (CI02). The assessment of all models resulted in all its item loadings being more than the recommended value of 0.5 (Fornell and Larcker 1981) (Bagozzi and Yi 1988), showing that the item indicator is a good measurement of the factor which is a good indicator of reliability.

5.2.2 Reliability – Internal Consistency

Internal consistency tests the reliability of a model by utilising Cronbach's Alpha and Composite Reliability.

5.2.2.1 Cronbach's Alpha

Cronbach's Alpha was used to estimate the extent to which all the factors were positively related to each other (Chapter 4 – Equation 4.1). It is suggested that a Cronbach's Alpha value greater than 0.7 indicates Indicator reliability (Nunnally and Bernstein 1978). The Cronbach's Alpha value calculated for the TPB model (Table 5.9) resulted in the lowest value for the factor perceived behavioural control (0.743) and the highest for effective use (0.934), and a low value of 0.887 for the factor perceived usefulness and highest value is 0.934 for effective use for the TAM model (Table 5.2), whereas the Cronbach's Alpha value for the ECM model (Table 5.3) are lowest for expectation (0.862) and highest for satisfaction (0.942). Cronbach's Alpha results for the Flow model (Table 5.4) show that the lowest value was for the factor perceived behavioural control (0.743) and highest was for the factor effective use (0.934). Table 5.5 shows that the lowest value was for the factor perceived behavioural control (0.743) and the highest value was for the factor skill (0.925) in the WST model. The Cronbach's Alpha value for the first possible model, ITU as shown in Table 5.6 shows that the lowest value was for the factor intention to use (0.915) and the highest value was for the factor effective use (0.934); whereas the second possible model, CU as shown in Table 5.7 reports the lowest value was for factor continuous intention (0.919) and the highest value was for the factor effective use (0.934). However, the newly Developed Model, Table 5.8 shows that the lowest value being for the factor continuous intention (0.919) and the highest value was for the factor satisfaction (0.942). An evaluation for bias on all models demonstrated an adequate reliability with values greater 0.70.

5.2.2.2 Composite Reliability

The Composite Reliability (CR) was also used as it is a higher estimate of true reliability (Chapter 4 – Equation 4.2). Internal consistency is indicated by a CR value greater than 70% (Gefen, Straub and Boudreau 2000). The CR for factors from the TPB model (Table 5.1) range from the lowest value of 0.829 to highest of 0.947; TAM model (Table 5.2) from a lowest value of 0.914 to a highest value of 0.947 for Effective Use; and the ECM model's CR values (Table 5.3) range from a lowest of 0.906 to a highest of 0.954. The CR for all factors in the Flow model (Table 5.5) has a minimum value of 0.825 and a maximum value of 0.947; and a minimum value of 0.937 and a maximum of 0.947 for the WST model (Table 5.6). The minimum CR value is 0.937 and the maximum value 0.947 for the ITU model (Table 5.6); and the minimum value is 0.947 and maximum is 0.949 for the CU model (Table 5.7); ranging from a lowest of 0.947 to a highest of 0.954 for the newly Developed Model (Table 5.8). The CR computations for all models was above 0.70 indicating adequate consistency. The overall lowest was 0.825 for perceived behavioural control and the overall highest being for satisfaction and continuous intention at a value of 0.954. The results also showed a higher estimate of values compared to the results from the Cronbach's Alpha computations.

Table 5. 1 – Measurement Model – Reliability of TPB

Factors	Items	Items Indicator Loadings	Cronbach's Alpha	Composite Reliability
Attitude	ATT01	0,815	0,91	0.928
	ATT02	0,845		
	ATT03	0,837		
	ATT04	0,646		
	ATT05	0,842		
	ATT06	0,846		
	ATT07	0,798		
Effective Use	EU01	0.779	0.934	0.947
	EU02	0.851		
	EU03	0.870		
	EU04	0.874		
	EU05	0.871		
	EU06	0.844		
	EU07	0.834		
Intention to Use	ITU01	0.820	0.915	0.937
	ITU02	0.863		
	ITU03	0.891		
	ITU04	0.894		
	ITU05	0.852		
Perceived Behavioural Control	PBC01	0.807	0.743	0.829
	PBC02	0.752		
	PBC03	0.537		
	PBC04	0.843		
Subjective Norm	SN01	0.815	0.873	0.908
	SN02	0.811		
	SN03	0.858		
	SN04	0.834		
	SN05	0.755		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than > 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 2 – Measurement Model – Reliability of TAM

Factors	Items	Items Indicator Loadings	Cronbach's Alpha	Composite Reliability
Attitude	ATT01	0.820	0.909	0.928
	ATT02	0.848		
	ATT03	0.836		
	ATT04	0.642		
	ATT05	0.843		
	ATT06	0.845		
	ATT07	0.794		
Effective Use	EU01	0.779	0.934	0.947
	EU02	0.851		
	EU03	0.870		
	EU04	0.874		
	EU05	0.871		
	EU06	0.844		
	EU07	0.834		
Intention to Use	ITU01	0.818	0.915	0.937
	ITU02	0.862		
	ITU03	0.892		
	ITU04	0.895		
	ITU05	0.853		
Perceived Ease of Use	PEOU01	0.879	0.929	0.946
	PEOU02	0.910		
	PEOU03	0.882		
	PEOU04	0.882		
	PEOU05	0.855		
Perceived Usefulness	PU01	0.872	0.887	0.914
	PU02	0.868		
	PU03	0.853		
	PU04	0.852		
	PU05	0.682		
	PU06	0.647		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than > 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 3 – Measurement Model – Reliability of ECM

Factors	Items	Items Indicator Loadings	Cronbach Alpha	rho_A	Composite Reliability
Continuous Intention	CI01	0.928	0.919	0.919	0.949
	CI02	0.951			
	CI03	0.904			
Confirmation	CONF01	0.888	0.885	0.885	0.929
	CONF02	0.912			
	CONF03	0.905			
Effective Use	EU01	0.778	0.934	0.935	0.947
	EU02	0.854			
	EU03	0.869			
	EU04	0.878			
	EU05	0.869			
	EU06	0.844			
	EU07	0.832			
Expectation	EXP01	0.856	0.862	0.873	0.906
	EXP02	0.880			
	EXP03	0.748			
	EXP04	0.875			
Satisfaction	SAT01	0.877	0.942	0.943	0.954
	SAT02	0.890			
	SAT03	0.892			
	SAT04	0.898			
	SAT05	0.874			
	SAT06	0.854			
Skill	SK01	0.794	0.925	0.926	0.939
	SK02	0.820			
	SK03	0.840			
	SK04	0.852			
	SK05	0.850			
	SK06	0.852			
	SK07	0.800			

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than > 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 4 – Measurement Model – Reliability of Flow Model

Factors	Items	Items Indicator Loadings	Cronbach's Alpha	Composite Reliability
Concentration	CON01	0.899	0.806	0.866
	CON02	0.821		
	CON03	0.750		
	CON04	0.660		
Effective Use	EU01	0.779	0.934	0.947
	EU02	0.851		
	EU03	0.870		
	EU04	0.874		
	EU05	0.871		
	EU06	0.844		
	EU07	0.834		
Intention to Use	ITU01	0.824	0.915	0.937
	ITU02	0.865		
	ITU03	0.891		
	ITU04	0.892		
	ITU05	0.848		
Perceived Behavioural Control	PBC01	0.831	0.743	0.825
	PBC02	0.722		
	PBC03	0.523		
	PBC04	0.840		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than > 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 5 – Measurement Model – Reliability of WST Model

Factors	Items	Items Indicator Loadings	Cronbach's Alpha	Composite Reliability
Attitude	ATT01	0.819	0.909	0.928
	ATT02	0.847		
	ATT03	0.833		
	ATT04	0.635		
	ATT05	0.848		
	ATT06	0.849		
	ATT07	0.795		
Effective Use	EU01	0.778	0.934	0.947
	EU02	0.854		
	EU03	0.869		
	EU04	0.878		
	EU05	0.869		
	EU06	0.844		
	EU07	0.832		
Intention to Use	ITU01	0.817	0.915	0.937
	ITU02	0.865		
	ITU03	0.892		
	ITU04	0.895		
	ITU05	0.851		
Perceived Behavioural Control	PBC01	0.831	0.743	0.825
	PBC02	0.722		
	PBC03	0.523		
	PBC04	0.840		
Skill	SK01	0.794	0.925	0.939
	SK02	0.820		
	SK03	0.843		
	SK04	0.851		
	SK05	0.849		
	SK06	0.852		
	SK07	0.798		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 6 – Measurement Model – Reliability of ITU Model

Factors	Items	Items Indicator Loadings	Cronbach's Alpha	Composite Reliability
Effective Use	EU01	0.779	0.934	0.947
	EU02	0.851		
	EU03	0.870		
	EU04	0.874		
	EU05	0.871		
	EU06	0.844		
	EU07	0.834		
Intention to Use	ITU01	0.821	0.915	0.937
	ITU02	0.862		
	ITU03	0.893		
	ITU04	0.894		
	ITU05	0.850		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 7 – Measurement Model – Reliability of CU Model

Factors	Items	Items Indicator Loadings	Cronbach Alpha	Composite Reliability (CR)
Continuous Intention	CI01	0.927	0.919	0.949
	CI02	0.951		
	CI03	0.904		
Effective Use	EU01	0.777	0.934	0.947
	EU02	0.851		
	EU03	0.870		
	EU04	0.879		
	EU05	0.867		
	EU06	0.846		
	EU07	0.835		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than 0.7 (Gefen, Straub and Boudreau 2000)

Table 5. 8 – Measurement Model – Reliability of Developed Model

Factors	Items	Items Indicator Loadings	Cronbach Alpha	Composite Reliability (CR)
Continuous Intention	CI01	0.928	0.919	0.949
	CI02	0.951		
	CI03	0.904		
Effective Use	EU01	0.778	0.934	0.947
	EU02	0.854		
	EU03	0.869		
	EU04	0.879		
	EU05	0.869		
	EU06	0.844		
	EU07	0.833		
Satisfaction	SAT01	0.878	0.942	0.954
	SAT02	0.891		
	SAT03	0.892		
	SAT04	0.897		
	SAT05	0.873		
	SAT06	0.854		

a. Indicator Reliability is indicated by item loading values greater than 0.5 (Hulland 1999)
b. Indicator Reliability identifies a Cronbach's alpha value larger than 0.7 (Nunnally and Bernstein 1978)
c. Internal Consistency is specified by CR values larger than 0.7 (Gefen, Straub and Boudreau 2000)

5.2.3 Convergent Validity

Convergent validity is determined by Average Variance Estimation (AVE) (Chapter 4 – Equation 4.3). It is recommended that all values be above the suggested 0.50 level thereby accounting for more than fifty percent of the variances observed (Fornell and Larcker 1981) (Bagozzi and Yi 1988). In the TPB model, the AVE values varied from 0.554 to 0.747 for (Table 5.9). The factor intention to use has the largest AVE value of 0.747 and perceived behavioural control recorded the least AVE value of 0.554. However, a study by (Tavallaee, Shokouhyar and Samadi 2017) showed the highest AVE value of perceived behavioural control. The lowest AVE value was 0.642 for the factor perceived usefulness and the highest was in TAM model for the factor perceived ease of use at 0.778 (Table 5.10). In the study by (Tavallaee, Shokouhyar and Samadi 2017) the AVE value for the factor perceived ease of use was much lower than the AVE value for perceived usefulness, however the AVE value for the factor attitude was same. The minimum value was 0.689 for skill and maximum value of 0.861 for the factor continuous intention in the ECM model (Table 5.11). The AVE values ranged from a low of 0.548 for perceived behavioural control to the highest value being 0.747 for intention to use in the Flow model (Table 5.12) as well as for the WST model (Table 5.13). The lowest value for the WST model was 0.651

for the factor attitude. Similarly, the least value recorded was 0.717 for the factor effective use in the ITU model (Table 5.14) and CU model (Table 5.15). The highest value was 0.747 for the factor intention to use in the ITU model and 0.861 for the factor continuous intention in the CU model. However, the AVE values for newly Developed Model ranged from 0.718 to 0.861 (Table 5.16) with the highest being for the factor continuous intention and lowest value recorded was 0.718 for effective use. The AVE results recorded were The AVE values were more than the suggested 0.50 level, which meant that more than half the variances observed in the items were accounted for by their hypothesised factors. This also shows that validity converges with a satisfactory result. So, this indicates that the measurement model is good, reliable, and valid. Therefore, it was found that there was adequate reliability and convergent validity for all factors in the measurement model.

Table 5. 9 – Convergent Validity of TPB

Factors	Average Variance Extracted (AVE)
Attitude	0.651
Effective Use	0.717
Intention to Use	0.747
Perceived Behavioural Control	0.554
Subjective Norm	0.665

- Convergent Reliability indicated by values more than 0.5 for AVE

Table 5. 10 – Convergent Validity of TAM

Factors	Average Variance Extracted (AVE)
Attitude	0.651
Effective Use	0.717
Intention to Use	0.747
Perceived Ease of Use	0.778
Perceived Usefulness	0.642

- Convergent Reliability indicated by AVE values larger than 0.5

Table 5. 11 – Convergent Validity of ECM

Factors	Average Variance Extracted (AVE)
Continuous Intention	0.861
Confirmation	0.813
Effective Use	0.717
Expectation	0.708
Satisfaction	0.776
Skill	0.689

- Convergent Reliability indicated by values more than 0.5 for AVE

Table 5. 12 – Convergent Validity of Flow Model

Factors	Average Variance Extracted (AVE)
Concentration	0.620
Effective Use	0.717
Intention to Use	0.747
Perceived Behavioural Control	0.548

- Convergent Reliability indicated by values greater than 0.5 for AVE

Table 5. 13 – Convergent Validity of WST Model

Factors	Average Variance Extracted (AVE)
Attitude	0.651
Effective Use	0.717
Intention to Use	0.747
Perceived Behavioural Control	0.548
Skill	0.689

- Convergent Reliability indicated by values greater than 0.5 for AVE

Table 5. 14 – Convergent Validity of ITU

Factors	Average Variance Extracted (AVE)
Effective Use	0.717
Intention to Use	0.747

- Convergent Reliability indicated by AVE values larger than 0.5 (Fornell and Larcker 1981; Bagozzi and Yi 1988)(Fornell and Larcker 1981; Bagozzi and Yi 1988)

Table 5. 15 – Convergent Validity of CU

Factors	Average Variance Extracted (AVE)
Continuous Intention	0.861
Effective Use	0.717

- Convergent Reliability indicated by values more than 0.5 for AVE

Table 5. 16 – Convergent Validity of Developed Model

Factors	Average Variance Extracted (AVE)
Continuous Intention	0.861
Effective Use	0.718
Satisfaction	0.776

- Convergent Reliability indicated by AVE values larger than 0.5

5.2.4 Discriminant Validity

Discriminant validity ensures that the item indicator actually measures that the factors that it is intended to measure (Chapter 4 – Equation 4.4). In this study, the discriminant validity measurement was conducted using the Cross Loadings Criterion and the Fornell-Larcker criterion (Fornell and Larcker 1981).

5.2.4.1 Cross Loadings Criterion

A Cross Loading ensured that indicator items employed in the questionnaire literally measured the factor and it was not confusing. This criterion reduces the presence of multi-collinearity among the factors, meaning that the item indicator does not load on more than one factor. The first criteria of the cross loading is to check that each item indicator loads the highest on that factor either horizontally or vertically.

The measurements on the TPB model (Table 5.17) show the item indicators ATT01, ATT02, ATT03, ATT04, ATT05, ATT06, and ATT07 are the highest for the factor attitude; EU01, EU02, EU03, EU04, EUO05, EU06, and EU07 are the highest for the factor effective use; ITU01, ITU02, ITU03, ITU04, and ITU05 the highest for the factor intention to use; PBC01, PBC02, PBC03, and PBC04 are the highest for the factor perceived behavioural control; and SN01, SN02, SN03, SN04, and SN05, are the highest for the factor subjective norm. In the TAM model, as shown in Table 5.18, the item indicators EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; ITU01, ITU02, ITU03, ITU04, and ITU05 are the highest for the factor intention to use; PEOU01, PEOU02, PEOU03, PEOU04 and PEOU05 are the highest for the factor perceived ease of use; and PU01, PU02, PU03, PU04, PU05 and PU06, are the highest for the factor perceived usefulness. ATT01, ATT02, ATT03, ATT05, ATT06, and ATT07 are the highest for the factor attitude, however the value for ATT04 (0.642) is lower than the values for the item measurements, PU01 (0.663), PU02 (0.677), PU03 (0.676) and PU04 (0.655) from the factor perceived usefulness. In the ECM model (Table 5.19), the item indicators CI01, CI02, and CI07 are the highest for the factor continuous intention; EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; CONF01, CONF02, and CONF03 are the highest for the factor confirmation; EXP01, EXP02, EXP03, and EXP04 are the highest for the factor expectation; SAT01, SAT02, SAT03, SAT04, SAT05, SAT06 and SAT07, are the highest for the factor satisfaction; and SK01, SK02, SK03, SK04, SK05, and SK06, are the highest for the factor skill.

In the Flow model (Table 5.20), the item indicators CON01, CON02, and CON03 are the highest for the concentration factor; whereas EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; ITU01, ITU02, ITU03, ITU04, and ITU05 the highest for the factor intention to use; and PBC01, PBC02, PBC03, and PBC04 are the highest for the factor perceived behavioural control. The WST model (Table 5.21), show the item indicators ATT01, ATT02, ATT03, ATT04, ATT05, ATT06, and ATT07 are the highest for the factor attitude; EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; ITU01, ITU02, ITU03, ITU04, and ITU05 are the highest for the factor intention to use; PBC01, PBC02, PBC03, and PBC04 are the highest for the factor perceived behavioural control; and SK01, SK02, SK03, SK04, SK05, SK06, and SN07, are the highest for the factor skill.

As shown in the ITU model (Table 5.22), the item indicators EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; and ITU01, ITU02, ITU03, ITU04, and ITU05 the highest with regard to the factor intention to use. As shown within the CU model (Table 5.23), the item indicators CI01, CI02, and CI07 are the highest for the factor continuous intention; and EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use. In the developed Model, as shown in Table 5.24, item indicators CI01, CI02, and CI03 are the highest for the factor continuous intention; EU01, EU02, EU03, EU04, EU05, EU06, and EU07 are the highest for the factor effective use; and SAT01, SAT02, SAT03, SAT04, SAT05, SAT06 and SAT07, are the highest for the factor satisfaction. The Cross Loading criterion results show that all item indicator measurements were higher for the associated factor than the item indicator measurement of all the other factors.

Table 5. 17 – Cross Loading criterion - Discriminant Validity – TPB

	Attitude	Effective Use	Intention to Use	Perceived Behavioural Control	Subjective Norm
ATT01	**0.815**	0.538	0.537	0.360	0.465
ATT02	**0.845**	0.584	0.570	0.358	0.513
ATT03	**0.837**	0.612	0.520	0.396	0.568
ATT04	**0.646**	0.423	0.339	0.274	0.412
ATT05	**0.842**	0.469	0.567	0.360	0.459
ATT06	**0.846**	0.471	0.538	0.368	0.474
ATT07	**0.798**	0.503	0.485	0.418	0.491
EU01	0.490	**0.779**	0.435	0.289	0.430
EU02	0.564	**0.851**	0.430	0.400	0.474
EU03	0.538	**0.870**	0.462	0.331	0.396
EU04	0.547	**0.874**	0.409	0.345	0.404
EU05	0.548	**0.871**	0.471	0.337	0.398
EU06	0.530	**0.844**	0.437	0.354	0.398
EU07	0.576	**0.834**	0.475	0.386	0.404
ITU01	0.507	0.449	**0.820**	0.356	0.425
ITU02	0.540	0.438	**0.863**	0.362	0.436
ITU03	0.530	0.456	**0.891**	0.331	0.363
ITU04	0.570	0.468	**0.894**	0.323	0.428
ITU05	0.593	0.468	**0.852**	0.338	0.439
PBC01	0.429	0.338	0.414	**0.807**	0.403
PBC02	0.302	0.312	0.214	**0.752**	0.302
PBC03	0.124	0.173	0.121	**0.537**	0.152
PBC04	0.377	0.358	0.321	**0.843**	0.351
SN01	0.497	0.408	0.421	0.361	**0.815**
SN02	0.458	0.361	0.339	0.331	**0.811**
SN03	0.522	0.436	0.400	0.362	**0.858**
SN04	0.493	0.406	0.385	0.361	**0.834**
SN05	0.472	0.378	0.422	0.347	**0.755**

Table 5. 18 – Cross Loading criterion - Discriminant Validity – TAM

	Attitude	Effective Use	Intention To Use	Perceived Ease of Use	Perceived Usefulness
ATT01	**0.820**	0.538	0.537	0.508	0.648
ATT02	**0.848**	0.584	0.570	0.468	0.673
ATT03	**0.836**	0.612	0.520	0.478	0.666
ATT04	**0.642**	0.423	0.339	0.346	0.465
ATT05	**0.843**	0.469	0.567	0.473	0.602
ATT06	**0.845**	0.471	0.539	0.509	0.588
ATT07	**0.794**	0.503	0.485	0.511	0.572
EU01	0.490	**0.779**	0.435	0.462	0.501
EU02	0.564	**0.851**	0.430	0.542	0.618
EU03	0.537	**0.870**	0.462	0.512	0.571
EU04	0.547	**0.874**	0.409	0.515	0.580
EU05	0.548	**0.871**	0.471	0.540	0.580
EU06	0.530	**0.844**	0.437	0.523	0.566
EU07	0.575	**0.834**	0.475	0.524	0.598
ITU01	0.509	0.449	**0.818**	0.425	0.490
ITU02	0.540	0.438	**0.862**	0.473	0.515
ITU03	0.531	0.456	**0.892**	0.471	0.510
ITU04	0.570	0.468	**0.895**	0.485	0.525
ITU05	0.594	0.468	**0.853**	0.454	0.522
PEOU01	0.526	0.526	0.502	**0.879**	0.584
PEOU02	0.519	0.533	0.472	**0.910**	0.553
PEOU03	0.516	0.564	0.454	**0.882**	0.545
PEOU04	0.489	0.519	0.470	**0.882**	0.548
PEOU05	0.532	0.551	0.458	**0.855**	0.564
PU01	0.663	0.614	0.547	0.556	**0.872**
PU02	0.677	0.606	0.533	0.530	**0.868**
PU03	0.676	0.596	0.487	0.488	**0.853**
PU04	0.655	0.609	0.503	0.536	**0.852**
PU05	0.451	0.383	0.403	0.492	**0.682**
PU06	0.417	0.382	0.343	0.466	**0.647**

__Table 5. 19 – Cross Loading criterion - Discriminant Validity - ECM__

	Continuous Intention	Confirmation	Effective Use	Expectation	Satisfaction	Skill
CI01	**0.928**	0.474	0.633	0.507	0.570	0.510
CI02	**0.951**	0.484	0.656	0.520	0.569	0.526
CI03	**0.904**	0.455	0.634	0.512	0.560	0.503
CONF01	0.462	**0.888**	0.542	0.601	0.536	0.581
CONF02	0.456	**0.912**	0.542	0.565	0.558	0.594
CONF03	0.456	**0.905**	0.533	0.556	0.573	0.623
EU01	0.560	0.500	**0.777**	0.431	0.615	0.519
EU02	0.552	0.539	**0.851**	0.469	0.677	0.612
EU03	0.604	0.499	**0.870**	0.445	0.628	0.569
EU04	0.594	0.484	**0.879**	0.406	0.648	0.570
EU05	0.569	0.527	**0.867**	0.468	0.669	0.589
EU06	0.591	0.490	**0.846**	0.441	0.614	0.575
EU07	0.621	0.504	**0.835**	0.468	0.662	0.626
EXP01	0.523	0.567	0.485	**0.856**	0.487	0.531
EXP02	0.509	0.534	0.460	**0.880**	0.474	0.528
EXP03	0.324	0.466	0.360	**0.748**	0.309	0.414
EXP04	0.480	0.567	0.458	**0.875**	0.448	0.468
SAT01	0.513	0.512	0.656	0.440	**0.877**	0.587
SAT02	0.531	0.533	0.667	0.447	**0.890**	0.591
SAT03	0.558	0.559	0.690	0.439	**0.892**	0.622
SAT04	0.523	0.548	0.659	0.470	**0.898**	0.616
SAT05	0.562	0.561	0.680	0.482	**0.874**	0.603
SAT06	0.538	0.542	0.670	0.454	**0.854**	0.607
SK01	0.430	0.525	0.548	0.458	0.541	**0.794**
SK02	0.454	0.557	0.568	0.464	0.576	**0.820**
SK03	0.531	0.594	0.609	0.562	0.635	**0.840**
SK04	0.447	0.541	0.539	0.438	0.534	**0.852**
SK05	0.443	0.558	0.574	0.503	0.565	**0.850**
SK06	0.452	0.558	0.582	0.497	0.589	**0.852**
SK07	0.450	0.521	0.557	0.436	0.539	**0.800**

Table 5. 20 – Cross Loading criterion - Discriminant Validity – Flow Model

	Concentration	Effective Use	Intention to Use	Perceived Behavioural Control
CON01	**0.899**	0.369	0.165	0.169
CON02	**0.821**	0.259	0.082	0.181
CON03	**0.750**	0.227	0.047	0.096
CON04	**0.660**	0.304	0.089	0.157
EU01	0.372	**0.779**	0.435	0.289
EU02	0.301	**0.851**	0.430	0.401
EU03	0.351	**0.870**	0.462	0.330
EU04	0.323	**0.874**	0.410	0.343
EU05	0.332	**0.871**	0.470	0.336
EU06	0.320	**0.844**	0.437	0.355
EU07	0.294	**0.834**	0.475	0.386
ITU01	0.114	0.449	**0.824**	0.363
ITU02	0.088	0.438	**0.865**	0.371
ITU03	0.132	0.456	**0.891**	0.334
ITU04	0.136	0.468	**0.892**	0.329
ITU05	0.144	0.468	**0.848**	0.344
PBC01	0.103	0.338	0.414	**0.831**
PBC02	0.208	0.312	0.214	**0.722**
PBC03	0.170	0.173	0.121	**0.523**
PBC04	0.176	0.358	0.321	**0.840**

Table 5. 21 – Cross Loading criterion - Discriminant Validity – WST Model

	Attitude	Effective Use	Intention to Use	Perceived Behavioural Control	Skill
ATT01	**0.819**	0.538	0.537	0.365	0.568
ATT02	**0.847**	0.584	0.570	0.361	0.575
ATT03	**0.833**	0.612	0.520	0.396	0.613
ATT04	**0.635**	0.423	0.339	0.274	0.429
ATT05	**0.848**	0.469	0.567	0.366	0.495
ATT06	**0.849**	0.471	0.538	0.373	0.545
ATT07	**0.795**	0.503	0.484	0.421	0.552
EU01	0.489	**0.779**	0.435	0.289	0.519
EU02	0.562	**0.851**	0.430	0.401	0.612
EU03	0.535	**0.870**	0.462	0.330	0.570
EU04	0.545	**0.874**	0.409	0.343	0.569
EU05	0.546	**0.871**	0.471	0.336	0.589
EU06	0.528	**0.844**	0.437	0.355	0.575
EU07	0.574	**0.834**	0.475	0.386	0.627
ITU01	0.510	0.449	**0.819**	0.363	0.452
ITU02	0.542	0.438	**0.862**	0.371	0.448
ITU03	0.532	0.456	**0.892**	0.334	0.452
ITU04	0.571	0.468	**0.894**	0.329	0.502
ITU05	0.595	0.468	**0.852**	0.344	0.495
PBC01	0.429	0.338	0.414	**0.831**	0.474
PBC02	0.299	0.312	0.214	**0.722**	0.365
PBC03	0.122	0.173	0.121	**0.523**	0.209
PBC04	0.376	0.358	0.321	**0.840**	0.478
SK01	0.548	0.549	0.407	0.425	**0.789**
SK02	0.568	0.568	0.428	0.459	**0.815**
SK03	0.632	0.610	0.530	0.460	**0.845**
SK04	0.548	0.539	0.442	0.456	**0.853**
SK05	0.549	0.574	0.470	0.477	**0.852**
SK06	0.549	0.582	0.464	0.441	**0.853**
SK07	0.482	0.557	0.402	0.447	**0.798**

Table 5. 22 – Cross Loading criterion - Discriminant Validity – ITU Model

	Effective Use	Intention to Use
EU01	**0.779**	0.435
EU02	**0.851**	0.430
EU03	**0.870**	0.462
EU04	**0.874**	0.409
EU05	**0.871**	0.471
EU06	**0.844**	0.437
EU07	**0.834**	0.475
ITU01	0.449	**0.821**
ITU02	0.438	**0.862**
ITU03	0.456	**0.893**
ITU04	0.468	**0.894**
ITU05	0.468	**0.850**

Table 5. 23 – Cross Loading criterion - Discriminant Validity – CU Model

	Continuous Intention	Effective Use
CI01	**0.927**	0.633
CI02	**0.951**	0.656
CI03	**0.904**	0.634
EU01	0.559	**0.777**
EU02	0.552	**0.851**
EU03	0.604	**0.870**
EU04	0.594	**0.879**
EU05	0.569	**0.867**
EU06	0.591	**0.846**
EU07	0.621	**0.835**

Table 5. 24 – Cross Loading criterion - Discriminant Validity – Developed Model

	Continuance Intention	Effective Use	Satisfaction
CI01	**0.928**	0.633	0.570
CI02	**0.951**	0.655	0.569
CI03	**0.904**	0.633	0.560
EU01	0.560	**0.778**	0.615
EU02	0.552	**0.854**	0.677
EU03	0.604	**0.869**	0.628
EU04	0.594	**0.879**	0.648
EU05	0.569	**0.869**	0.669
EU06	0.591	**0.844**	0.614
EU07	0.621	**0.833**	0.662
SAT01	0.513	0.656	**0.878**
SAT02	0.531	0.668	**0.891**
SAT03	0.558	0.690	**0.892**
SAT04	0.523	0.659	**0.897**
SAT05	0.562	0.681	**0.873**
SAT06	0.538	0.671	**0.854**

5.2.4.2 Fornell-Larcker Criterion

The Fornell-Larcker criterion table provides an estimation of the square root of AVE, which appears in the diagonal cells. If the square root of AVE (uppermost number) in the factor column is greater than values below it, then there is discriminant validity (Fornell and Larcker 1981). Each of the factors has low correlation with each other hence there is good discriminant validity. The Fornell-Larcker Criterion was assessed for all models. The TPB model (Table 5.25) shows the highest value was 0.864 for intention to use, and the lowest value was 0.744 for perceived behavioural control; the TAM model (Table 5.26) shows the highest value was 0.882 for perceived uase of Use, and the lowest 0.801 for perceived usefulness; and the ECM model (Table 5.27) shows the highest value was 0.902 for confirmation and the lowest was 0.830 for skill. The Flow (Table 5.28) and WST (Table 5.29) models indicate the highest value to be 0.864 for intention to use and the lowest value to be 0.740 for perceived behavioural control. However, the ITU model (Table 5.30) shows a lowest value for the factor intention to use at 0.847 and highest value to be 0.864 for intention to use, and the lowest was 0.847 for effective use. The CU model (Table 5.31) and new developed Model (Table 5.32) indicated the lowest result of 0.847 and the highest value of 0.928 for continuous intention. The results in Table 5.4 showed sufficient discriminant validity indicated by the square roots of the AVE's which were larger than its corresponding correlation coefficients. In summary, this study has demonstrated adequate reliability, convergent validity, and discriminant validity for the measurement model.

Table 5. 25 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity - TPB

	Attitude	Effective Use	Intention to Use	Perceived Behavioural Control	Subjective Norm
Attitude	**0.807**				
Effective Use	0.641	**0.847**			
Intention to Use	0.635	0.528	**0.864**		
Perceived Behavioural Control	0.451	0.412	0.395	**0.744**	
Subjective Norm	0.600	0.489	0.485	0.433	**0.815**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 26 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity -TAM

	Effective Use	Intention To Use	Perceived Ease of Use	Perceived Usefulness	Attitude
Effective Use	**0.847**				
Intention To Use	0.528	**0.864**			
Perceived Ease of Use	0.611	0.534	**0.882**		
Perceived Usefulness	0.678	0.593	0.634	**0.801**	
Attitude	0.64	0.636	0.586	0.751	**0.807**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 27 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity - ECM

	Confirmation	Continuous Intention	Effective Use	Expectation	Satisfaction	Skill
Confirmation	**0.902**					
Continuous Intention	0.508	**0.928**				
Effective Use	0.597	0.691	**0.847**			
Expectation	0.636	0.553	0.528	**0.841**		
Satisfaction	0.616	0.610	0.761	0.517	**0.881**	
Skill	0.665	0.553	0.685	0.580	0.686	**0.830**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 28 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity – Flow Model

	Concentration	Effective Use	Intention to Use	Perceived Behavioural Control
Concentration	**0.787**			
Effective Use	0.387	**0.847**		
Intention to Use	0.142	0.528	**0.864**	
Perceived Behavioural Control	0.198	0.412	0.403	**0.740**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 29 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity – WST Model

	Attitude	Effective U	Intention	Perceived	Skill
Attitude	**0.807**				
Effective Use	0.638	**0.847**			
Intention to Use	0.637	0.528	**0.864**		
Perceived Behavioural Control	0.454	0.412	0.402	**0.740**	
Skill	0.670	0.686	0.545	0.545	**0.830**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 30 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity – ITU Model

	Effective Use	Intention to Use
Effective Use	**0.847**	
Intention to Use	0.528	**0.864**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 31 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity – CU Model

	Continuous Intention	Effective Use
Continuous Intention	**0.928**	
Effective Use	0.691	**0.847**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

Table 5. 32 – Fornell-Larcker Criterion Analysis for Checking Discriminant Validity – Developed Model

	Continuance Intention	Effective Use	Satisfaction
Continuance Intention	**0.928**		
Effective Use	0.690	**0.847**	
Satisfaction	0.610	0.762	**0.881**

- The elements are square roots of AVE represented diagonally, in bold; others are correlation coefficients.

5.3 Structural model

The structural model evaluates the relationship between the hypothesised factors. The structural model was assessed for multi-collinearity, the model fit, determination of the coefficient, the relationship strength between factors, as well as for predictive relevance tests.

5.3.1 Collinearity

The structural model specifies the relationships among the unobserved factors, and according to Schumacker and Lomax (2010) it therefore tests for collinearity, which is the inter-correlation between two or more independent factors. This study used a reflective model, hence the inner variance inflation factor (VIF) coefficients were assessed for each model to check if the VIF values between the factors were below the cutoff value 5. According to Table 5.33, the VIF of the TBP factors (attitude, effective use, and intention to use, subjective norm, and perceived behavioural control) were below the cutoff value of 5. The highest coefficient was 1.681. The VIF inner values were assessed between the TAM factors (Effective Use, Intention to Use, Perceived Ease of Use, Perceived Usefulness and Attitude), as indicated in Table 5.34, the highest inner VIF value was 1.672. The inner VIF values of the ECM model were assessed to check if the values between the factors (confirmation, continuous intention, effective use, expectation, satisfaction, and skill) were below 5. According to Table 5.35, the highest coefficient was 1.680.

The inner values were assessed for the Flow model to check if the VIF values between the factors (concentration, effective use, intention to use, perceived behavioural control) were below 5. According to Table 5.36, the highest coefficient was 1.041. The inner values were assessed for the WST model to check if the VIF values between the factors (Attitude, Effective Use, and Intention to Use, Perceived Behavioural Control, and Skill) were below 5. According to Table 5.37, the highest coefficient was 2.092 for skill. The inner values were assessed for the ITU model to check if the VIF values between the factors (effective use, and intention to use) were below 5. As stated in Table 5.38, the highest coefficient was 1.000. The inner values were assessed for the CU model to check if the VIF values between the factors (continuous intention, and effective use) were below 5. According to Table 5.39, the highest coefficient was 1.000. The inner values were assessed to check if the variance inflations factor values between the factors (satisfaction, effective use, and intention to use) were below 5. As stated in Table 5.40, the highest coefficient was 1.594. The VIF values for all models were below 5, meaning there is no strong indication of multi-collinearity between factors.

Table 5. 33 – Inner VIF Values - TPB

	Attitude	Effective Use	Intention to Use	Perceived Behavioural Control	Subjective Norm
Attitude			1.681		1.255
Effective Use					
Intention to Use		1.000			
Perceived Behavioural Control	1.000		1.324		1.255
Subjective Norm			1.649		

Table 5. 34 – Inner VIF Values - TAM

	Effective Use	Intention To Use	Perceived Ease of Use	Perceived Usefulness	Attitude
Effective Use					
Intention To Use	1.000				
Perceived Ease of Use					1.672
Perceived Usefulness					1.672
Attitude		1.000			

Table 5. 35 – Inner VIF Values - ECM

	Confirmation	Continuous	Effective U	Expectation	Satisfaction	Skill
Confirmation					1.680	
Continuous Intention			1.000			
Effective Use						
Expectation	1.506				1.680	
Satisfaction		1.000				
Skill	1.506					

Table 5. 36 – Inner VIF Values – Flow Model

	Concentration	Effective Use	Intention to Use	Perceived Behavioural Control
Concentration			1.041	
Effective Use				
Intention to Use		1.000		
Perceived Behavioural Control			1.041	

Table 5. 37 – Inner VIF Values – WST Model

	Attitude	Effective Use	Intention to Use	Perceived Behavioural Control	Skill
Attitude			1.851		
Effective Use					
Intention to Use		1.000			
Perceived Behavioural Control			1.452		
Skill			2.092		

Table 5. 38 – Inner VIF Values – ITU Model

	Effective Use	Intention to Use
Effective Use		
Intention to Use	1.000	

Table 5. 39 – Inner VIF Values – CU Model

	Continuous Intention	Effective Use
Continuous Intention		1.000
Effective Use		

Table 5. 40 – Inner VIF Values – Developed Model

	Effective Use	Satisfaction	Continuance Intention
Effective Use			
Satisfaction	1.594		1.000
con int	1.594		

5.3.2 Inner Model Path

The inner model was assessed for path coefficient sizes and significance. TPB's inner model suggests that Intention to Use has a strong effect on effective use (0.528) and subjective norm, and perceived behavioural control are weak predictors for intention to use. It also demonstrates that the factor attitude has the strongest impact on intention to use (0.506), however subjective norm (0.134) and perceived behavioural control (0.110) have weak influences on intention to use. However, a study by (Cheon *et al.* 2012) also showed that subjective norm had a weak influence on the behavioural intention but attitude and perceived behavioural control had a strong impact on the factor behavioural intention.

Attitude is a strong predictor of subjective norm (0.508), as well as of perceived behavioural control on attitude (0.451). The factor perceived behavioural control has moderate effect on subjective norm (0.204). The hypothesised path relationship between attitude and intention to use, perceived behavioural control and intention to use and subjective norm and intention to use is statistically significant. Also, the hypothesised path relationship between attitude and subjective norm, as well as perceived behavioural control and subjective norm is statistically significant.

TAM's inner model suggests that intention to use has a strong impact on effective use (0.528). The inner model demonstrates that attitude has the strongest influence on intention to use (0.636), and therefore the hypothesised path relationship between attitude and intention to use (H1) is statistically significant. The hypothesised path relationship between perceived usefulness and attitude (H4) is of statistical importance (0.634) but the hypothesis path relationship between perceived ease of use and attitude (H3) is weak (0.184). The study by (Cheon *et al.* 2012) had similar results between the factors perceived usefulness and attitude however the study by (Tavallaee, Shokouhyar and Samadi 2017) had a negative effective between perceived usefulness and attitude but favorable impact on the factors ease of use and attitude. It can be concluded that attitude is a moderately strong predictor of intention to use. Perceived usefulness indirectly affects the factor intention to use through attitude.

The inner model of ECM suggests that continuous intention has the strongest effect on effective use (0.691). The inner model also shows the factor satisfaction to have a strong influence on continuous intention (0.610). Skill has a moderately strong effect on confirmation (0.446), and confirmation has a moderately strong effect on satisfaction (0.483). Expectation has a moderate effect on confirmation (0.378), and on satisfaction (0.210). The hypothesised path relationships between continuous intention and effective use, satisfaction and continuous intention, skill and confirmation as well as confirmation and satisfaction is statistically outstanding. The hypothesised path relationships between expectation and satisfaction, and expectation and confirmation is also moderately significant. The factor skill indirectly affects satisfaction through confirmation, and indirectly affects continuous intention through satisfaction. The factors expectation and confirmation indirectly affect continuous intention through satisfaction.

The inner model for flow suggests that the factor intention to use has a strong impact on effective use (0.528) as well as suggesting that perceived behavioural control has a stronger influence on Intention to use (0.390), than concentration (0.065). The hypothesised path relationship between perceived behavioural control and intention to use is statistically significant, whereas the relationship between perceived behavioural control and intention to use is very weak. The inner model demonstrates that intention to use has the strongest impact on effective use (0.528). The inner model of WST proposes that attitude has the strongest influence on intention to use (0.480), followed by skill (0.174) and perceived behavioural control (0.090). A hypothesised path relationship between skill and intention to use as well as the factors perceived behavioural control and intention to use are statistically weak. In conclusion the hypothesized path connection between attitude and intention to use is statistically strong. The inner model of ITU suggests that Intention to Use has a strong impact on effective use (0.528), which concludes that its hypothesised path relationship is statistically significant. The inner model of CU suggests that continuous intention has a strong effect on effective use (0.691). The hypothesised path relationship between continuous intention and effective use is statistically significant. The inner model of the developed model suggests that continuous intention has a strong effect on effective use (0.359). The inner model proposes that satisfaction has the strongest effect on continuous intention (0.610). The hypothesised path association between satisfaction and effective use is statistically notable at 0.543. In conclusion, the factors continuous intention and satisfaction are moderately strong predictors of intention to use.

5.3.3 Model Fit

The model fit was evaluated using SRMR and NFI for all models (Chapter 4, Equation 4.7 and 4.8). The extent to which the sample variance-covariance data fit the structural equation model was determined using SRMR and NFI. The SRMR model fit value for the TPB was 0.053 suggesting a good fit, whereas the NFI model fit value was 0.87 suggesting a less than marginal model fit. In the TAM model, the SRMR model fit value was 0.048, which is a good fit as it falls below the cutoff of 0.8. The NFI model fit value was 0.876 suggesting a less than marginal model fit as the cutoff is 0.9. In the ECM model, the SRMR model fit evaluation result was 0.040, which meets the recommended cutoff value less than 0.8. The NFI model fit evaluation result was 0.893 suggesting an almost marginal model fit as it almost meets the recommended cutoff criteria of being 0.90 and greater. In the flow model, the SRMR model fit value was 0.053 suggesting a good fit, whereas the NFI model fit value was 0.870 suggesting a less than marginal model fit. In the WST model, the SRMR model fit value was 0.046 suggesting a good fit, whereas the NFI model fit value was 0.930 suggesting marginal model fit being within the range of 0.90 to 0.95. In the ITU model, the SRMR model fit value was 0.044 suggesting a good fit, whereas the NFI model fit value was 0.937 suggesting marginal model fit which is above the 0.90 recommended cut-off value. In the CU model, the SRMR model fit value was 0.038 suggesting a good fit, whereas the NFI model fit value was 0.927 suggesting marginal model fit.

5.3.4 R-Square

The coefficient of determination, also called R-squared or R^2, assesses how well the model fits thedata. R^2 values can range from the values 0 to 1. Nevertheless, a bigger value means a better indication of predictive accuracy of the factors for the effective use of smartphones for m-learning. In the structural model, the path coefficients were examined and the variance explained by each path correlations on effectively using smartphones for m-learning in different models used (Chapter 4, Equation 4.9). The TPB R^2 values (Table 5.41) are checked for attitude, effective use, intention to use and subjective norm and seem moderately fine, but quite weak for attitude which signified the proportion of variance of the exogenous factors on the endogenous factors. The R^2 value is 0.279 for the endogenous factor effective use. In the TPB model, the factor intention to use almost moderately explains 27.9% of the variance in effective use. The factors attitude, subject norm, and perceived behavioural control together account for 42.9% of the variance in intention to use. The factors attitude, and perceived behavioural control together explain 39.4% of the variance of subjective norm. The factor perceived behavioural control weakly explains 20.3% of the variance of attitude, where a value less than 0.25 is considered weak. Intention to use, subjective norm and attitude are considered to be both independent and dependent factors.

In TAM, the R^2 values are checked for effective use, intention to use and attitude. Effective use (0.279) and intention to use (0.405) are within the range of 0 and 1, which seem moderately adequate, however attitude (0.584), which signifies more than 50% of the proportion of variance of the exogenous factors on the endogenous factors, has a stronger predictive accuracy (Table 5.42). The endogenous factor, effective use, has a R^2 value of 0.279. The factor intention to use moderately describes 27.9% of the variance in effective use for the TAM model. Factors attitude explains 40.5% of the variance in intention to use. The factors perceived usefulness and perceived ease of use together explain 58.4% of the variance of attitude. Intention to use, and attitude are considered to be both independent and dependent factors. The ECM R^2 values are checked for confirmation, continuous intention, effective use and satisfaction (Table 5.43). The R^2 value for confirmation is 0.536, which signifies 50% of the proportion of variance of the exogenous factors on the endogenous factors. The R^2 values for continuous intention, effective use and satisfaction are moderate. The R^2 value is 0.478 for the factor effective use. The factor continuous intention moderately explains 47.8% of the variance in effective use for the ECM model. The factor satisfaction explains 37.3% of the variance in continuous intention. The factors expectation and confirmation together describe 40.6% of the variance of satisfaction. Factors expectation and skill together explains 53.6% of the variance of confirmation. Continuous intention, satisfaction, and confirmation are considered to be both independent and dependent factors.

The R^2 for the Flow model indicates that the values intention to use and effective use seems moderately fine, but very weak for intention to use, which signifies the proportion of variance of the exogenous factors on the endogenous factors (Table 5.44). The R^2 value is 0.278 for the endogenous factor effective use. This means that the factor intention to use almost moderately explains 27.8% of the variance in effective use in the Flow model. The factors concentration, and perceived behavioural control together explain 16.7% of the variance in intention to use. Intention to use is considered to be both an independent and dependent factor. The WST model R^2 values (Table 5.45) are checked for Intention to use and effective use. The R^2 value for effective use is 0.279 and intention to use is 0.437, which signifies less than 50% of the proportion of variance of exogenous factors on endogenous factors. The R^2 is 0.279 for the effective use endogenous factor in the WST model. This means that the factor intention to use almost moderately explains 27.9% of the variance in effective use. The factors attitude, skill, and perceived behavioural control together explain 43.7% of the variance in intention to use. Intention to use is considered to be both an independent and dependent factor. The ITU model R^2 values are checked for effective use (Table 5.46). The R^2 value for effective use is 0.279, which signifies the proportion of variance of the exogenous factors on the endogenous factors. The R^2 values for effective use is moderate. The R^2 is 0.279 for the effective use endogenous factor. In the ITU model, the factor intention to use moderately accounts for 27.9% of the variance in effective use. Intention to Use is an independent factor and effective use is a dependent factor. The CU model R^2 values are checked for effective use (Table 5.47). The R^2 value for effective use is 0.478, which signifies a just below 50% of the proportion of variance of the exogenous factors on the endogenous factors.

The R^2 values for Effective Use is moderate. The R^2 is 0.478 for the Effective Use endogenous factor meaning that the factor intention to use moderately explains 47.8% of the variance in effective use in the CU model. In the Developed Model, the R^2 values were examined for endogenous factors continuous intention and effective Use, and found to have a moderate effect (Table 5.48). The R^2 value for effective use is 0.661 which signifies more than 50% of the proportion of variance of exogenous factors on endogenous factors. The R^2 value is 0.661 for the effective use endogenous factor. This suggests that the factor continuous intention and satisfaction explains 66.1% of the variance in effective use in the developed model. The factor satisfaction explains 37.3% of the variance in continuous intention. The R^2 value for TPB, TAM, WST and ITU models was the same at 0.279 and 0.278 for the Flow model, whereas the R^2 value for ECM and CU was 0.478. The highest R^2 value was for the newly Developed Model at 0.661.

Table 5. 41 – R-Square Values - TPB

	R Square
Attitude	0.203
Effective Use	0.279
Intention to Use	0.429
Subjective Norm	0.394

Table 5. 42 – R-Square Values - TAM

	R Square
Effective Use	0.279
Intention To Use	0.405
Attitude	0.584

Table 5. 43 – R-Square Values - ECM

	R Square
Confirmation	0.536
Continuous Intention	0.373
Effective Use	0.478
Satisfaction	0.406

Table 5. 44 – R-Square Values – Flow Model

	R Square
Effective Use	0.278
Intention to Use	0.167

Table 5. 45 – R-Square Values – WST Model

	R Square
Effective Use	0.279
Intention to Use	0.437

Table 5. 46 – R-Square Values – ITU Model

	R Square
Effective Use	0.279

Table 5. 47 – R-Square Values – CU Model

	R Square
Effective Use	0.478

Table 5. 48 – R-Square Values – Developed Model

	R Square
Continuance Intention	0.373
Effective Use	0.661

5.3.5 Bootstrapping

A bootstrapping procedure was conducted to generate t-statistics values for significance testing. An approximate t-statistic value for significance measurement of the structural path is estimated by obtaining a large amount of subsamples from the initial sample as well as some extra samples to provide bootstrap standard errors, which is achieved by means of a bootstrapping process. This study used a two-tailed t-test with a subsample size 1000, and a significance level of 5 percent. As shown in Table 5.49 (TPB), the highest t-statistic values was 15.861 and the lowest value is 2.874. The t-statistic values are all above 1.96, indicating that the path coefficients are significant. As shown in Table 5.50 for TAM, the highest t-statistic value was 19.065 for the path coefficients attitude to intention to use. The t-statistic values are all above 1.96, which means that the path coefficients is significant. ECM (Table 5.51) shows that the highest t-statistic value was 24.585 for the path coefficients continuous intention to effective use. The t-statistic values are all above 1.96, suggesting that the path coefficients is significant. As shown in Table 5.52 (Flow model), the highest t-statistic value was 14.913 for the path coefficients intention to use to effective use.

The t-statistic values are all above 1.96 demonstrating that the path coefficients are significant. As shown in Table 5.53 (WST model), the highest t-statistic value was 16.017 for the path coefficients intention to use to effective use. The t-statistic values are all above 1.96, which means that the path coefficients are significant. As shown in Table 5.54 (ITU model), the t-statistic value was 14.829 for the path coefficients intention to use to effective use. The t-statistic values are all above 1.96, which means that the path coefficients are significant. As shown in Table 5.55 (CU model), the t-statistic value was 24.975 for the path coefficients continuous intention to effective use. The t-statistic values are all above 1.96 which means that the path coefficients are significant. As shown in Table 5.56 (developed model), the highest t-statistic value was 24.585 for the path coefficients continuous intention to effective use. The t-statistic values are all above 1.96, which means that the path coefficients are significant.

5.3.6 Effect size

The strength of the relationship between the factors showing the amount the exogenous factor contributes to the endogenous factor's R^2 value was determined by measuring the effect size (f^2). The effect size was calculated manually (Chapter 4, Equation 4.10). According to (Cohen 1988), a value of 0.35 and over is considered to have a large effect size. A value 0.15 to 0.35 is considered to have a medium effect size, and a value for 0.02 to 0.15 indicates a small effect size. Table 5.49 demonstrates the quality of a effect size of the model factors. Attitude to effective use has a large effect size. Attitude to subjective norm has an extremely high to moderate effect. Attitude to intention to use, perceived behavioural control to attitude and perceived behavioural control to subjective norm have moderate effect sizes, however, perceived behavioural control to intention to use, and subjective norm to intention to use have small effect sizes. With the use of the R^2 value, the effect size was calculated (Table 5.50). The strength between the factors attitude to intention to use, intention to use to effective use, and perceived usefulness to attitude have large effect sizes however perceived ease of use to attitude have a small effect size (0.048). Attitude to intention to use had substantial strength (0.681).

The results on the strength between the factors Confirmation to Satisfaction, Continuous Intention to Effective Use, Expectation to Confirmation, Expectation to Satisfaction, Satisfaction to Continuous Intention, and Skill to Confirmation are shown in Table 5.51. Satisfaction to Continuous Intention has a large effect size (0.916). The effect size for Confirmation to Satisfaction, Expectation to Confirmation, and Skill to Confirmation has a moderate effect size. However, Expectation to Satisfaction has a small effect size. The strength between the factors Confirmation to Satisfaction, Continuous Intention to Effective Use, Expectation to Confirmation, Expectation to Satisfaction, Satisfaction to Continuous Intention, and Skill to Confirmation have been accessed (Table 5.52) and Satisfaction to Continuous Intention has a large effect size. Confirmation to Satisfaction, Expectation to Confirmation, and Skill to Confirmation have moderate effect sizes. However, Expectation to Satisfaction has an extremely small effect size falling below the recommended cutoff value of 0.02.

According to Table 5.53, the strength between the factors Intention to Use and Effective Use have a large effect size, and Attitude to Intention to Use has a medium effect size. Skill to Intention to Use has a moderate effect size. However, Perceived Behavioural Control to Intention to Use has an extremely small effect size falling a lot below the recommended cutoff value of 0.02. According to Table 5.54, the strength between the factors Intention to Use to Effective Use has a large effect size. The strength between the factors Continuous Intention and Effective Use has an extremely large effect size (Table 5.55). The strength between the factors Continuous Intention to Effective Use, Satisfaction to Continuous Intention, and Satisfaction to Effective Use resulted in Satisfaction to Continuous Intention as well as Satisfaction in Effective Use having large effect sizes (Table 5.56). The effect size for Continuance Intention to Effective Use has a moderate effect size.

5.3.7 Predictive Relevance

Predictive relevance (Q^2) is assessed using a blindfolding procedure. This procedure calculates the exogenous way of looking at whether the datasets can actually work on its own when data or multiple endogenous numbers of omission distance can still have a strong predictive value on the endogenous factor (Chapter 4, Equation 4.11). According to (Henseler et al 2009), a recommended value of 0.35 and over is considered to have a large predictive effect. A value 0.15 to 0.35 is considered to have a medium predictive effect, and a value for 0.02 to 0.15 indicates a small predictive effect.

Attitude to intention to use has a very small to medium predictive effect, whereas attitude to subjective norm has a very medium to large predictive effect (Table 5.49). Intention to use to effective use, perceived behavioural control to attitude, and perceived behavioural control to subjective norm have a moderate predictive effect. The predictive relevance between perceived behavioural control and intention to use have a small predictive effect, but subjective norm to intention to use is very weak. Attitude to intention to use has a large predictive effect, whereas intention to use to effective use and perceived usefulness have a moderate predictive effect (Table 5.50). The perceived ease of use to attitude (0.019) had an extremely small predictive effect. Continuous intention to effective use, and satisfaction to continuous intention have large predictive effects, whereas skill to confirmation has a moderate predictive effect (Table 5.51). Confirmation to satisfaction, expectation to confirmation, and expectation to satisfaction had small predictive effects.

Concentration to intention to use (0.003) has extremely weak predictive effect as it falls below the recommended cutoff value of 0.02 (Table 5.52). Intention to use to effective use (0.277), and perceived behavioural control to intention to use (0.114) have moderate predictive effects, falling within the recommended range of 0.02 and 0.150. The factors intention to use and effective use have moderate predictive effect, and from attitude to intention to use has a small predictive effect (Table 5.53). Both perceived behavioural control to intention to use and skill to intention to use have extremely small predictive effects. Intention to use to effective use has a moderate predictive effect (Table 5.54). Continuous intention to effective use have a large predictive effect (Table 5.55). Continuous Intention to effective use, and satisfaction to continuous intention have large predictive effects, whereas skill to confirmation has a moderate predictive effect (Table 5.56). Confirmation to satisfaction, expectation to confirmation, and expectation to satisfaction had small predictive effects.

5.3.8 Hypothesis Testing

H1, H2, H3, H4, H5, H6 and H7 have been supported in TPB as shown in Table 5.49 , however H5 and H7 have the weakest predictive effect on effectively using smartphones for m-learning. The highest standardised beta value, t-Statistic value, f^2 value and q^2 value was for H3.

Table 5. 49 – Direct Relationships for Hypothesis testing - TPB

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Attitude -> Intention to Use	0,504	0,045	11,160**	Supported	0,263	0,149	0,428	0,579	0.000
H2	Attitude -> Subjective Norm	0,51	0,039	13,118**	Supported	0,340	0,169	0,446	0,574	0.000
H3	Intention to Use -> Effective Use	0,529	0,033	15,861**	Supported	0,387	0,227	0,474	0,581	0.000
H4	Perceived Behavioural Control -> Attitude	0,45	0,036	12,699**	Supported	0,255	0,139	0,389	0,502	0.000
H5	Perceived Behavioural Control -> Intention to Use	0,111	0,037	2,946*	Supported	0,014	0,007	0,047	0,174	0.003
H6	Perceived Behavioural Control -> Subjective Norm	0,203	0,042	4,866**	Supported	0,056	0,026	0,133	0,27	0.000
H7	Subjective Norm -> Intention to Use	0,134	0,046	2,874*	Supported	0,016	0,007	0,059	0,21	0.004

** indicates p < 0.01, * indicates p < 0.05
TPB's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
TPB's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al (2009)

H1, H2, H3, and H4 have been supported in TAM as shown in Table 5.50, but H3 had the smallest predictive impact on the effective use of smartphone for m-learning. The highest standardised beta value, t-Statistic value, f^2 value and q^2 value was for H1.

Table 5. 50 – Direct Relationships for Hypothesis testing - TAM

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Attitude -> Intention To Use	0,637	0,033	19,065**	Supported	0,681	0,393	0,58	0,685	0.000
H2	Intention To Use -> Effective Use	0,529	0,034	15,323**	Supported	0,387	0,227	0,472	0,584	0.000
H3	Perceived Ease of Use -> Attitude	0,185	0,046	4,015**	Supported	0,048	0,019	0,11	0,258	0.000
H4	Perceived Usefulness -> Attitude	0,634	0,043	14,848**	Supported	0,577	0,222	0,558	0,699	0.000

**p<0.01; *p<0.05
TAM's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values:" 0.35 (large). 0.15 (medium), 0.02 (small)";
TAM's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

H1, H2, H3, H4, H5 and H6 have been supported in ECM as shown in Table 5.51, however H4 had the smallest predictive impact on effectively using smartphones for m-learning. The highest standardised beta value, t-Statistic value, f^2 value and q^2 value was for H2, which was quite substantial.

Table 5. 51 – Direct Relationships for Hypothesis testing - ECM

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Confirmation -> Satisfaction	0,482	0,049	9,792**	Supported	0,229	0,140	0,402	0,563	0,000
H2	Continuous Intention -> Effective Use	0,692	0,028	24,585**	Supported	0,916	0,466	0,645	0,736	0,000
H3	Expectation -> Confirmation	0,38	0,046	8,176**	Supported	0,246	0,124	0,303	0,457	0,000
H4	Expectation -> Satisfaction	0,21	0,052	4,017**	Supported	0,044	0,027	0,122	0,295	0,000
H5	Satisfaction -> Continuous Intention	0,612	0,037	16,545**	Supported	0,595	0,435	0,546	0,668	0,000
H6	Skill -> Confirmation	0,444	0,045	9,987**	Supported	0,282	0,172	0,372	0,518	0,000

**p<0.01; *p<0.05
ECM's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
ECM's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

H2, and H3 have been supported in the Flow model as shown in Table 5.52, however H1 is not supported. It has no significant influence with a t-statistic value below 1.96 and the weakest predictive impact on effectively using smartphones for anytime learning. The standardised beta, the t-statistic value, f^2 and q^2 is the highest for H2.

Table 5. 52 – Direct Relationships for Hypothesis testing – Flow Model

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Concentration -> Intention to Use	0.076	0.040	1.648	Unsupported	0,005	0,003	0,018	0,135	0,100
H2	Intention to Use -> Effective Use	0.529	0.035	14.913**	Supported	0,385	0,227	0,470	0,589	0,000
H3	Perceived Behavioural Control -> Intention to Use	0.386	0.039	10.125**	Supported	0,176	0,114	0,323	0,447	0,000

**p<0.01, *p<0.05
Flow model's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
Flow model's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

H1, H2, H3, and H4 is favorable in WST model as shown in Table 5.53, however H3 had the smallest predictive influence on the effective use of smartphone for m-learning. The highest standardised beta value, T-Statistic value, f^2 value and q^2 value was for H2.

Table 5. 53 – Direct Relationships for Hypothesis testing – WST Model

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Attitude -> Intention to Use	0,48	0,048	10,024**	Supported	0,222	0,125	0.404	0,561	0,000
H2	Intention to Use -> Effective Use	0,529	0,033	16,017**	Supported	0,387	0,227	0.476	0,581	0,000
H3	Perceived Behavioural Control -> Intention to Use	0,093	0,036	2,469**	Supported	0,009	0,006	0.035	0,158	0,014
H4	Skill -> Intention to Use	0,172	0,051	3,422**	Supported	0,025	0,014	0.087	0,258	0,001

**p<0.01; *p<0.05;
WST's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
WST's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

H1 has been supported in the ITU model as shown in Table 5.54. The highest standardised beta value, T-Statistic value, f^2 value are quite high and statistically significant.

Table 5. 54 – Direct Relationships for Hypothesis testing – ITU Model

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Intention to Use -> Effective Use	0,528	0,036	14,829**	Supported	0,387	0,227	0,468	0,584	0,000

**p<0.01, *p<0.05
ITU's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
ITU's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

H1 has been supported in the CU model as shown in Table 5.55. The standardised beta value, T-Statistic value, f^2 value and q^2 value was quite substantial for H1.

Table 5. 55 – Direct Relationships for Hypothesis testing – CU Model

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Continuous Intention -> Effective Use	0,691	0,028	24,795**	Supported	0,916	0,466	0,644	0,735	0,000

**p<0.01, *p<0.05
CU's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small);
CU's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al (2009)

H1, H2, and H3 in the new Developed Model, as shown in Table 5.56, have been supported; however H3 had the smallest predictive effect on effectively using smartphones for anywhere learning. The highest standardised beta value, T-Statistic value, f^2 value and q^2 value was for H2.

Table 5. 56 – Direct Relationships for Hypothesis testing – Developed Model

Hypothesis	Relationship	Std Beta	Std Error	T-Statistic	Decision	f2	q2	95%CILL	95%CIUL	P Values
H1	Continuance Intention -> Effective Use	0,355	0,046	7,727	Supported	0,236	0,097	0,279	0,431	0,000
H2	Satisfaction -> Continuance Intention	0,612	0,036	17,165	Supported	0,595	0,435	0,55	0,668	0,000
H3	Satisfaction -> Effective Use	0,546	0,043	12,577	Supported	0,540	0,220	0,475	0,619	0,000

**p<0.01; *p<0.05
Developed model's R2 values (Attitude = 0.203; Intention to Use = 0.429; Subjective Norm = 0.394, Effective Use = 0.279);
f2 recommended values: "0.35 (large). 0.15 (medium), 0.02 (small)";
Developed model's Q2 values (Attitude = 0.122; Intention to Use = 0.297; Subjective Norm = 0.244, Effective Use = 0.185);
Q2 recommended values: 0.35 (large). 0.15 (medium), 0.02 (small) according to Henseler et al. (2009).

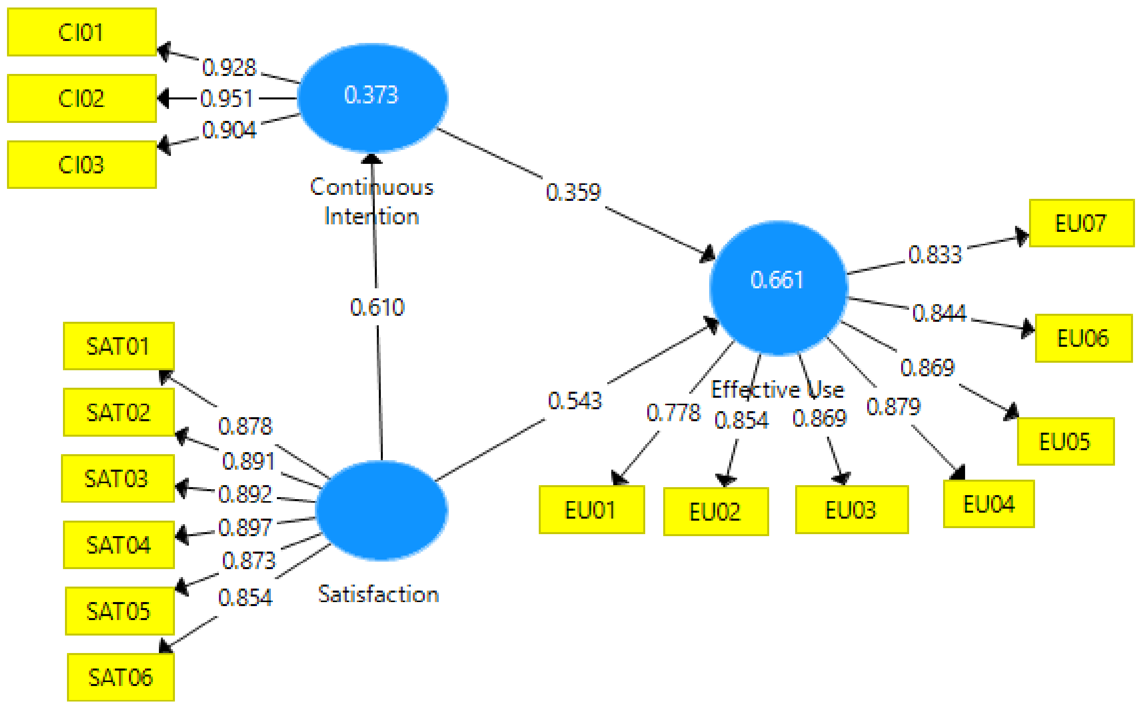

Figure 5. 1 – Developed Model

5.4 Discussion

Question 1: What are the identified factors influencing the effective use of smartphones for m-learning?

The aim of the research was to examine the predictors on the effective utilization of smartphones for m-learning. Firstly, factors influencing the effective use of smartphones for m-learning needed to be identified. Based on the TPB model, the factors attitude, subjective norm, and perceived behavioural control definitely influences the intention to use smartphones effectively for m-learning. The factors perceived usefulness and perceived ease of use from the TAM model positively influences attitude towards the intention to effectively utilise smartphone for m-learning. According to the ECM model, the factors expectation, confirmation, and skill positively influences one's satisfaction on the continuous intention to effectively use smartphones for m-learning. Based on Flow model, the intention to effectively use smartphones for m-learning is positively influenced by the factors concentration and perceived behavioural control. Based on the WST model, the factors attitude, skill, and perceived behavioural control positively influences the intention to use smartphones effectively for m-learning. There were thirteen factors from the above mentioned models that were selected.

Question 2: What are the interdependencies or relationships between the identified factors influencing the effective use of smartphones for m-learning?

The variance explained (R^2) was 27.9% for TPB, TAM, and the WST models and 27.8% for the Flow model. The variance explained (R^2) was 47.8% of the ECM model. Intention to use had a much smaller variance explained than continuance intention. In the TPB model, attitude has a positive influence on the intention to use smartphones effectively. Subjective norm positively influences the intention to use smartphones effectively. Perceived behavioural control positively influences the intention to use smartphones effectively. Perceived behavioural control also positively influences the attitude towards the effective use of smartphones for m-learning. Behavioural control positively influences the subjective norms towards the effective use of smartphones for m-learning. This indicates a positive attitude towards the intention of effectively using smartphones for m-learning. In the TPB model, attitude strongly predicts the intention to use. However, perceived behavioural control does not have a great impact on the intention to use, but it is a strong predictor of attitude. attitude influences a student's positive attitude, which in turn influences subjective norm (SN), but SN is not a very strong predictor of intention to use, as students may feel that their lecturers and classmates don't encourage them in the use of smartphones for m-learning. In the TAM model, attitude positively influences the intention to effectively use smartphones for m-learning. Perceived usefulness firmly influences attitude to effectively use smartphones for m-learning. Perceived ease of use also positively influences the attitude to effectively use smartphones for m-learning. This indicates the acceptance of effectively using smartphones for m-learning. Perceived usefulness is a strong predictor of attitude. Perceived ease of use also has a significant influence on attitude, demonstrating an initial adoption of smartphones for m-learning, where students are at ease and quite proficient in effectively using the smartphone for m-learning. Whereas, if students find it useful, this may influence their intention or attitude to use it or not. The factor attitude is also a strong predictor of the intention to use in TAM model.

For the ECM model, expectation positively influences satisfaction. Confirmation of student's expectation together with skill also positively influences satisfaction. If students are satisfied, they will be positively influenced to continuously use smartphones effectively in m-learning. This indicates that satisfaction positively influences the continuous and effective implementation of smartphones for m-learning. Skill has been added to the ECT model to understand an individual's effective use of smartphone for m-learning. The results demonstrate that the student expectations and skill (competence) of actual effective use predicts confirmation. Confirmation impacts on satisfaction as well as on expectation of confirmed utilization of smartphones for m-learning. A strong predictor of a student's continuous application of smartphones for m-learning is satisfaction, which is similar to findings by (Bhattacherjee 2001).

In the Flow model, it has been found that concentration does not support the intention to use smartphones effectively, as indicated by its t-statistic, f2 and q2 values, which were all below the recommended cut-off value. This indicates that concentration did not influence students to effectively use their smartphones for m-learning. Concentration has been added to the Flow model to predict effective use of smartphone for m-learning. In this model, perceived behavioural control is a strong predictor of Intention to use, compared to concentration. This could mean that the level of absorption in using smartphones for m-learning is not so high nor does it strongly impact or influence the use. However, PBC might be greatly influencing the intention to use as issues such as network, data, and infrastructure might not be in the hands of the student. In the WST model, attitude and skill emphatically effects the aim of using technology effectively. In the ITU model the strongest predictor is attitude, which could demonstrate the importance of having an optimistic attitude towards the use of smartphones for m-learning. Skill and perceived behavioural control are also not strong predictors of intention to use, according to the TPB theory on attitude. Attitude is a very strong predictor of the factor intention to use in the TPB, TAM, Flow and WST models, according to the theory by (Ajzen 1985). However, PBC seem to be a strong predictor in the Flow model than in the WST model. Satisfaction is a very strong predictor of continuous intention, according to Expectation Continuance Theory. Both the intention to use and continuous intention positively influences the effective utilization of smartphones for learning at any location.

Question 3: What model can be developed to better explain factors that predict the effective use of smartphones for m-learning?

Intention to use explained 27.9% of the variance of effective use, which is the same results for the TPB, TAM, and WST models tested. Continuous intention explains 47.8% of the variance of the effective use, which is the same results from the ECM model. The new developed model has two independent factors to predict the effective implementation of smartphones for studying at any location. It is a parsimonious model, which simply predicts the effective use of smartphones. It was found that continuous intention and satisfaction together explained 66.1% of effective use. The variance explained for the Developed Model is much higher than all the other models where R^2 is 66.10 percent. All the models used had many factors explaining the same amount of the overall variance on the effective use of smartphones for m-learning, making it quite complex. Therefore, the development of a new model looked at developing and testing two new models, which comprised one independent factor only, for each. The first new model used the independent factor, intention to use, whereby 27.9% of the variance was explained, which is similar to results from the models TPB, TAM, Flow and WST. The second new model used the independent factor, continuous intention, whereby 47.8% of the overall variance was explained. This is similar to the results obtained from the ECM model.

Another possible new model was tested using different predictors, which resulted in the newly Developed Model. It was discovered that satisfaction and continuous intention predict the effective use of smartphones for m-learning. Satisfaction and continuous intention together explained 66.10% of the variance. The factor loadings examined, are factors with values greater than 0.7 indicating a strong relationship between them. The Cronbach's alpha as well as the Composite Reliability result showed extremely good internal consistency. The AVE was greater than the recommended value of 0.5 showing good convergent validity (Fornell and Larcker 1981) (Bagozzi and Yi 1988) and even the square root of the AVE was greater than the values of the rows and columns whereby discriminate validity shows the appropriateness for all the structures. R^2 value for effective use is 0.661. Continuous intention and satisfaction explain 66.10% of effective use. Adding other factors to this model increased the R^2 value slightly, but not over 70 percent.

The β coefficient of H1, implying the effect of continuous intention on effective use of smartphones in m-learning, equals to 0.610. The β coefficient of H2, implies that the effect of satisfaction on continuous intention to use smartphones for m-learning is equal to 0.359. The β coefficient of H3, implying the effect of satisfaction on effective utilization of smartphones in m-learning is equal to 0.543. According to β coefficient representing the factor loading is each hypothesis test, path coefficient, adequate effect size, and adequate predictive relevance. The positive factor loading indicates the importance of that relationship and the acceptance of hypothesis, one can conclude that all the hypothesis presented in this research have strong and important relations. Continuous intention and satisfaction have positive influences on effectively using smartphones for m-learning. Satisfaction also positively impacts on continuous intention and effective use of smartphones for m-learning. In conclusion, this new developed model consisting of the factors satisfaction, continuous intention and effective use is a good model to explain the variance, as well as a parsimonious model that uses a simple way of explaining the effective use of smartphones for m-learning. Our new model shows that university students who are satisfied with the fulfilment of their expectations towards the technology are most likely to continuously and effectively use smartphones in m-learning hence enabling them to achieve academic success.

5.5 Conclusion

This chapter discussed the findings obtained from the analysis. The TPB, TAM, ECM, Flow and WST were tested for reliability and validity. An assessment of the multi-collinearity, model fit, determination of coefficient, the relationships between factors, as well as predictive relevance tests were conducted on the structural model and found to be good predictors on the effective use of smartphones for m-learning. A new Developed Model was developed after investigating these models. The new Developed Model found satisfaction, continuous intention to use and effective use to be good predictors for the effective use of smartphones for m-learning. The final chapter summarises the study, states its shortcomings, as well as provide additional recommendations on research in the future.

Chapter 6:

Summary, Limitations, Recommendations and Conclusion

This chapter presents the summary of the research aims, limitations, thereafter the study's suggested recommendations for studies in the future then provides a concluded discussion.

6.1 Summary

The aim of this study was to examine the factors that affect the use of smartphones for mobile learning. To achieve this particular study aim a number of existing theories of technology adoption were investigated. These theories were selected because of their popularity in the literature. They include the theory of planned behaviour (TPB), technology acceptance model (TAM), expectation confirmation model (ECM), flow theory, and will, skill and tool model (WST).

Firstly, with the use of the TPB, TAM, ECM, Flow and WST models, thirteen factors were identified as factors impacting the effectiveness of m-learning by means of smartphones. These factors include attitude, perceived usefulness, perceived ease of use, subjective norm, perceived behavioural control, confirmation, expectation, satisfaction, skill, concentration, intention to use, continuous intention and effective use.

Secondly, the results of structural equation modelling confirmed a significant impact of all factors except the factor of concentration. Then attitude is a strong predictor of intention to use, but a strong predictor of attitude are the factors perceived behavioural control and perceived usefulness. However, concentration, perceived ease of use, skill, perceived behavioural control and subjective norm does not have a great impact on the intention to use. Skill indirectly influences satisfaction through confirmation, which strongly predicts satisfaction. Expectation has a significant influence on satisfaction. Satisfaction is a very strong predictor of continuous intention, which is according to the expectation continuance theory.

Thirdly, a comprehensive and parsimonious model for the effective use of smartphones for the m-learning in which the independent factors, continuous intention and satisfaction were proposed. This model extends the understanding of the concept of satisfaction in the effective use of smartphones for m-learning. Moreover, it adds to the limited literature available on effective use.

6.2 Limitations

This research has achieved its objective in addition to answering the research questions, however, the study does have some limitations. This study has been conducted in only one department, the Department of Information Technology in the Durban University of Technology (DUT), a university in Durban, South Africa. South Africa is made up of many traditional universities, universities of technology, private colleges as well as Training and Vocational Education and Training (TVET) colleges. Thus, the results from this research cannot be generalised for all universities at different geographical locations. A huge number of students that participated in the survey are from underprivileged backgrounds and may not have sufficient skills in the use technology for m-learning hence they may have experienced dissatisfaction in the learning process. Even though there are various makes and types of smartphones available, all students do not have the same smartphones. Some may have had faster, more powerful smartphones, which can impact on student experience, satisfaction as well as motivation to use m-learning.

6.3 Recommendations

Future research could extend the findings of this study by including students at other faculties and departments at the DUT or alternatively other traditional and technology universities in South Africa. An investigation of other factors that will influence the effective use of smartphones for m-learning should be conducted. Further studies are recommended to confirm the results of this study either in other departments at DUT or as well as other universities in South Africa.

Future research could also extend to the perceptions of instructors on the factors affecting and contributing towards m-learning. It should also focus on whether resources and applications made available to students are positively impacting on achieving academic success. Actual test results of students before and after using the resources for m-learning should be researched. Future research should also focus on factors affecting management’s efforts on implementing proper infrastructures for m-learning.

6.4 Conclusion

This study was the first to examine the way in which various conceptual models can predict the effective utilization of smartphones for learning on the move. It has developed and produced a more, specific, yet parsimonious model, with a greater predictive ability. The key challenge was how best to encourage and motivate students to take advantage of the many possibilities available for learning. Students need to find satisfaction in continuously and effectively using smartphones for m-learning to achieve academic success. The results indicate that while post-acceptance continue to influence user's continuous intention to use, satisfaction with respect to previous use or expectation has a comparatively stronger influence than the factor continuous intention to use on the dependent factor effective use of smartphones. User satisfaction is determined mainly by the user's confirmation of expectation from their past usage and consequently influenced by perceived usefulness and skill.

Hence, this study makes a contribution to the information system continuance model, by confirming that the argument on the strength of user satisfaction to predict continuance theoretically was reinforced by usage habit. The findings of this study are helpful for university administrators, application developers, device manufacturers, as well as network service providers. The research findings on teaching, planning, and resource allocation at institutional levels must be considered by educators, administrators and policy makers. Against the changes in the use of technology, research on student satisfaction and their continuous use of smartphones for m-learning will become more important. The findings suggest that for the success of effective use of smartphones for m-learning at university level, management should focus on enhancing student satisfaction as this impacts on the continuous use of technology and into effective use of devices for m-learning. Students are ideal candidates for m-learning. Universities should focus on improving learning skills associated with the use of smartphones for m-learning. University management should focus on improving infrastructures, or data plans that will enable mobile devices to be productively and constructively used by students for acquiring knowledge wherever they maybe located. Academic staff should also encourage the use of smartphones for learning purposes.

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Appendix A

FACULTY OF ACCOUNTING AND INFORMATICS, DURBAN UNIVERSITY OF TECHNOLOGY

INVESTIGATING STUDENT PERCEPTIONS ON EFFECTIVE USE OF SMARTPHONES FOR MOBILE LEARNING

Survey

In this survey, you are kindly required to fully answer all questions to the best of your knowledge. Please provide an appropriate response to each sub-question by writing or marking the right option that best describe the extent of your usage of smartphones for mobile learning (m-learning).

PART ONE

What is your demographic information, please write / mark accordingly?

a. Age ………..

b. Gender Male……………………………………… Female …………………………………………………..

c. Location Urban……………………… Rural…………………… Semi-rural…………………….

d. Level of Study: First-year ………… Second-year ……….. Third-year ………… Fourth-year ………..

e. Ownership: Do you own any of these mobile devices? Tick the appropriate choice/s.

Smartphone | iPad | Tablet | iPod | PDA

What do you use your smartphone for?

Study purposes ___________ Entertainment purposes ______________

How long have you been using your smartphone for mobile learning (m-learning)?

Not used | 1 to 4 weeks | 1 to 3 months | 4 to 6 months

7 to 11 months | 1 to 3 years | Greater than 3 years

Do you have an Internet Contract? Yes………………….. No……………………………

PART 2

Please read each question carefully. Please answer each of the following questions by circling the number that best describes your opinion.

[Intention to Use]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
I intend to use smartphones for m-learning on a regular basis in the future.	1	2	3	4	5	6	7
I plan to use smartphone for m-learning in the future.	1	2	3	4	5	6	7
I prefer to use smartphone for m-learning in the future.	1	2	3	4	5	6	7
I like to use smartphone for m-learning in the future.	1	2	3	4	5	6	7
I will strongly recommend that others use smartphones for m-learning.	1	2	3	4	5	6	7

[Expectation]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
If I use smartphones for m-learning, I will increase my effectiveness on the task.	1	2	3	4	5	6	7
If I use smartphones for m-learning, I will gather complete and timely information.	1	2	3	4	5	6	7
If I use smartphones for m-learning, my peers will perceive me as competent.	1	2	3	4	5	6	7
If I use smartphones for m-learning, I will increase my sense of accomplishment.	1	2	3	4	5	6	7

[Confirmation]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
My experience with using smartphones for m-learning was better that what I expected.	1	2	3	4	5	6	7
The service provided by the m-learning system for using smartphones was better than I expected.	1	2	3	4	5	6	7
Overall, most of my expectations from using smartphones for m-learning were confirmed	1	2	3	4	5	6	7

[Attitude]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
Using smartphones for m-learning allows me to get my work done more quickly.	1	2	3	4	5	6	7
Using smartphones for m-learning helps me gain a better understanding of the content of my courses.	1	2	3	4	5	6	7
Using smartphones for m-learning helps me to do well and get high marks in my courses.	1	2	3	4	5	6	7
Using smartphones for m-learning helps me to interact with the instructor and other students in class.	1	2	3	4	5	6	7
Using smartphones for m-learning is a good idea.	1	2	3	4	5	6	7
It is a good idea to apply m-learning using smartphones.	1	2	3	4	5	6	7
It is fun to work with m-learning using smartphones.	1	2	3	4	5	6	7

[Subjective norm]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
Most people who are important to me think that it would be a good idea to use smartphones for m-learning.	1	2	3	4	5	6	7
My instructors think that I need to regularly use smartphones for m-learning.	1	2	3	4	5	6	7
My class colleagues think that I need to regularly use smartphones for m-learning.	1	2	3	4	5	6	7
My close friends think that I need to regularly use smartphones for m-learning.	1	2	3	4	5	6	7
My university encourages me to regularly use smartphones for m-learning.	1	2	3	4	5	6	7

[Perceived behaviour control]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
I have what it takes to use smartphone for m-learning.	1	2	3	4	5	6	7
I have sufficient data bundles available while using my smartphone for m-learning.	1	2	3	4	5	6	7
I can afford the device and data costs.	1	2	3	4	5	6	7
I am entirely in control of using my smartphone for m-learning.	1	2	3	4	5	6	7

[Perceived usefulness]

Sub-questions	Strongly Disagree(1)	2	3	4	5	6	Strongly Agree (7)
Using smartphones for m-learning helps me achieve learning success.	1	2	3	4	5	6	7
Using smartphones for m-learning promotes good learning practices.	1	2	3	4	5	6	7
Using smartphones for m-learning improves my performance academically.	1	2	3	4	5	6	7
Using smartphones for m-learning allows me to get my work done more quickly.	1	2	3	4	5	6	7
Using smartphones for m-learning enables me to get information anywhere at any time.	1	2	3	4	5	6	7
Using smartphones for m-learning helps me collaborate instantly with colleagues about anything I am not sure about.	1	2	3	4	5	6	7

[Skill]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
I am able to perform the most difficult of tasks on the smartphone for m-learning.	1	2	3	4	5	6	7
I have found easier ways to complete and access the tasks on the smartphone for m-learning.	1	2	3	4	5	6	7
I am motivated to perform well by using the smartphone for m-learning.	1	2	3	4	5	6	7
I explore new uses of the smartphone to support my task for m-learning.	1	2	3	4	5	6	7
I often experiment with new ways of using the smartphone to accomplish my tasks on m-learning.	1	2	3	4	5	6	7
I often find new uses of the smartphone in performing my task for m-learning.	1	2	3	4	5	6	7
I use the smartphone in novel ways to complete my tasks for m-learning.	1	2	3	4	5	6	7

[Perceived ease of use]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
It is easy to use smartphones for m-learning.	1	2	3	4	5	6	7
It is simple to use smartphones for m-learning.	1	2	3	4	5	6	7
It is convenient to smartphones for m-learning.	1	2	3	4	5	6	7
It is easy to use smartphones to access information in m-learning.	1	2	3	4	5	6	7
Using smartphones for m-learning is user-friendly.	1	2	3	4	5	6	7

[Concentration]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
When using my smartphone for m-learning I forget about the people around me.	1	2	3	4	5	6	7
When using my smartphone for m-learning I am not unaware of my surroundings.	1	2	3	4	5	6	7
When using my smartphone for m-learning I forget about my time.	1	2	3	4	5	6	7
I am not distracted by other social software application on my smartphone while m-learning.	1	2	3	4	5	6	7

[Satisfaction]

Sub-questions	Strongly Disagree(1)	2	3	4	5	6	Strongly Agree (7)
I am satisfied with effectively using smartphones for m-learning.	1	2	3	4	5	6	7
I am satisfied with using smartphones for m-learning.	1	2	3	4	5	6	7
I am pleased with the experience of using smartphones for m-learning.	1	2	3	4	5	6	7
I am contented with using smartphones for m-learning.	1	2	3	4	5	6	7
I am delighted with using smartphones for m-learning.	1	2	3	4	5	6	7
I feel very confident with using smartphone for m-learning.	1	2	3	4	5	6	7

[Effective Use]

Sub-questions	Strongly Disagree (1)	2	3	4	5	6	Strongly Agree (7)
Using smartphone for m-learning has changed my learning habit.	1	2	3	4	5	6	7
Using smartphone for m-learning has improved my academic performance.	1	2	3	4	5	6	7
Using smartphone for m-learning has improved my ability to engage.	1	2	3	4	5	6	7
Using smartphone for m-learning has improved my ability in accomplishing my tasks.	1	2	3	4	5	6	7
Using smartphone for m-learning has allowed me to accomplish my tasks in much more exciting and interesting ways.	1	2	3	4	5	6	7
Using smartphone for m-learning has allowed me to accomplish more tasks in less time.	1	2	3	4	5	6	7
Using smartphone for m-learning has made me more creative and innovative in my learning.	1	2	3	4	5	6	7

[Continuous Intention]

Sub-questions	Strongly Disagree(1)	2	3	4	5	6	Strongly Agree(7)
I will use smartphones for m-learning on a regular basis in the future.	1	2	3	4	5	6	7
I will frequently use smartphone for m-learning in the future.	1	2	3	4	5	6	7
I will strongly recommend that others use smartphones for m-learning.	1	2	3	4	5	6	7