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Research Report

A model for the acceptance and use of mHealth in South Africa: A UTAUT and TTF perspective

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I declare that this is my own unaided work and is, to the best of my knowledge and belief, original, except as acknowledged in the text.

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Signed: LG Mongwe
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Abstract

Scaling up high impact community based mHealth interventions is one of the agenda items mentioned in the National Digital Health Strategy of South Africa for the period 2019 -2024. Although many mHealth interventions have been explored, many of them end up in the pilot phase and do not reach full implementation. A common theme which was found as a possible driver of scalability is designing an mHealth application that considers usability and acceptability by users. The purpose of this study was to synthesize a model for the acceptance and use of mHealth in the South African health sector. A positivist research approach was used to test the adoption factors using the Task-Technology Fit (TTF) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Seven factors that could potentially impact the adoption of mHealth technology in South Africa were tested. The data for the study was collected through an online survey questionnaire which was shared through social media platforms. Results of this study were used to answer questions related to factors that have an impact on the adoption of mHealth applications in the health sector in South Africa. The study found that when adoption factors were combined into the UTAUT and TTF model, the only factor that was significant was facilitating conditions. The study findings in this regard were not consistent with other studies and it is therefore recommend that other scholars explore the reasons for these differences. The other factors were found to be significant when bivariate regression was used to compare the factors to the dependant variable of user acceptance and use of mHealth technology.

The study further found that the combined model of Task Technology Fit has a positive impact on the adoption of mHealth technology in South Africa. The implication of the finding is that mHealth designers should build the functionalities of the innovation with the idea of making the task that the innovation supports easier to perform.

Keywords: IT Adoption, mHealth adoption, mHealth, User Acceptance, TTF and UTAUT

CHAPTER 1: INTRODUCTION TO THE STUDY

1.1 Background

In 2018, 10% percent of the world's population owned a smart phone. More than 41 000 health related applications were available on Google Play store in 2017 (*Healthcare Apps Available Google Play 2021*, n.d.). There were over 53 000 health related Apps on Google Play store and Apple store as at the first quarter of 2021 (*Healthcare Apps Available Google Play 2021*, n.d.). The difference between quarter 1 of 2017 and quarter 1 of 2021 shows a significant increase. The computational power of mobile phones has improved such that they can be leveraged to improve the health care sector (Balapour et al., 2019). These are just some of the indicators of the rapid growth of this technology.

mHealth is defined as the use of technology to support health care services through the use of voice calls, SMS messaging systems, wireless transmission of data and mobile phone applications (Osei & Mashamba-Thompson, 2021). mHealth is a subset of telehealth and can also simply be defined as the use of portable technology to perform health related services and interventions (Lu et al., 2021). mHeath interventions include treatment support, diagnosing support, health monitoring, data accuracy and many other inventions that can support the health sector (Osei & Mashamba-Thompson, 2021). These interventions go beyond patient care. They also provide support to health care professionals and the health sector by facilitating the collection and sharing of data (Qudah & Luetsch, 2019). They also offer some level of independence and involvement on the part of the patient as they empower patients to be actively involved in their care and to receive information that provides actionable actions that they can take with regards to their health care (Qudah & Luetsch, 2019). Some examples of mHealth applications include healthy living applications, symptom checking applications, medication reminder applications etc.

A study conducted in 2019 stated that even though the adoption of mHealth technology is widely discussed, there is a gap in terms of predicting the intention to accept and use this mHealth technology (Balapour et al., 2019). Many mHealth applications have been built in South Africa even though many of them remain as part of pilot studies (Ojo, 2018).

The purpose of the study was to synthesise a model which can be used to explain the acceptance and use of mHealth in South Africa. The model was based on the Unified Theory of Technology Acceptance and Use of Technology (UTAUT) together with the Task-Technology Fit (TTF) model. This was with the aim of

trying to mitigate one of the issues that hinder the usage of mHealth applications at a larger scale, building an application with usability in mind. The report will be broken down into six Chapters. Chapter 1 will provide insight into the problem that the research aimed to address and will introduce the research topic and chapter 2 will be a literature review to better understand topics that have been researched related to the research topic. Chapter 3 will be a discussion on the research methodology used to address the problem. Then chapter 4 will be a presentation of the results and Chapter 5 will be an in-depth discussion of the results and how to interpret them. Chapter 6 will be the conclusion which will summarize the findings, implications of study for academia and for the industry. Research limitations and future research will also be discussed in Chapter 6.

1.2 Problem Statement

Even though many mHealth applications have been developed in South Africa most of them remain as part of pilot studies and are not fully accepted and used (Ojo, 2018; Latif et al., 2017). A study which focused on mHealth interventions in developing countries found that most mHealth interventions do not move beyond the pilot phase and further suggested that national health policies should include scalability and sustainability as important success measures for an mHealth intervention (Latif et al., 2017). Another study which aimed to summarize the challenges that must be overcome for an mHealth intervention to move from pilot phase to full-scale adoption found that one of the challenges that must be overcome is that mHealth applications must be built with usability in mind (Wallis et al., 2017). Scaling up high impact community based mHealth interventions is one of the agenda items mentioned in the National Digital Health Strategy of South Africa for the period 2019 -2024, indicating a further gap in the area of scaling up (*NDoH,2019*).

Although there are many mHealth interventions which proved to have the potential to improve the health system and services provided, many of them end up at the pilot phase (Ojo, 2018). Many studies have mentioned that to enjoy the benefits that come with mHealth, policies that are aimed at resolving innovation challenges at scale should be explored. Most current studies related to mHealth technology are related to pilot projects (Said, 2022), thus motivating for further studies on the adoption of mHealth technology.

The study aimed to synthesise a model for the acceptance and use of mHealth by individual users in South Africa which can be used to better understand the factors that can increase the chances of an mHealth innovation moving beyond the pilot phase.

The factors impacting the adoption of mHealth in South Africa are still under-investigated and not fully understood, and this limits the understanding of factors that cause mHealth innovations to not move beyond the pilot phase. The problem statement provides a motivation for the development of the model and to further understand the factors that impact mHealth adoption.

1.3 Research Questions and Objectives

The purpose of the study was to synthesise a model that can be used to explain the acceptance and use of mHealth at the individual user level. The model was based on the UTAUT and TTF theories of technology acceptance and use.

1.3.1 Research Questions

The questions that the study aimed to answer were as follows:

Primary Research Question

RQ1: What are the factors that affect the use and acceptance of mHealth applications by individual adult users in the South African health sector?

Secondary Research Questions

RQ2: What are the technology characteristics that affect the use and acceptance of mHealth in the South African health sector by adults?

RQ3: What are the task characteristics that affect the use and acceptance of mHealth in the South African health sector by adults?

RQ4: Which behavioural constructs influence an individual user's decision to use and accept a mHealth in the South African health sector by adults?

1.3.2 Research Objectives

This section contains the goals and objectives of the study. They are listed below:

RO1: To review existing literature to identify UTAUT and TTF factors that are dominant in the adoption mHealth technology.

RO2: To identify the factors that affect the acceptance and use of mHealth in the South African health sector.

RO3: To determine the significant factors in the UTAUT and TTF models that affect the adoption of mHealth in the South African health sector.

RO4: To potentially conceptualize a model for the adoption of mHealth in the South African context.

1.4 Delimitations

1. The study participants were limited to the province of Gauteng in South Africa.
2. The study was limited to adult participants who are over the age 18.
3. The study was not focused on a specific type of mobile health application but rather on any mobile health application in the health sector.

CHAPTER 2: LITERATURE REVIEW

2.1 mHealth Technology

mHeath technology can be defined as software that is installed in mobile devices such as a phone, smart phone, tablet etc. (Kumar et al., 2018). It is a subset of e-health and includes the use of mobile phones, tablets, smart watches for health related services, health information and data collection (Pai & Alathur, 2021). It enhances access to health related information for both patients and health care providers, and assists with remote patient care, health related data collection which leads to timely health care decisions and recommendations (Hood et al., 2016). mHealth can interact with the health system itself, health care providers and patients in improving the quality of health care (Osei & Mashamba-Thompson, 2021). mHealth technology has been recognized as playing a pivotal role in the surveillance and monitoring of infectious diseases such as Ebola, HIV, SARS and most recently COVID-19 (Osei & Mashamba-Thompson, 2021). The role that mHealth played in supporting the surveillance on the mentioned infectious diseases is an indicator of the increasing growth and impact of this technology.

mHealth has also been studied as a possible health solution in managing chronic illnesses such as diabetes, epilepsy, hypertension indicating that mHealth could possibly play an important role in the management of diseases. In the use of diabetes self-management, one study found that there were too many mHealth applications which were overwhelming for users (Hood et al., 2016). This is different to other studies which found that there were too few applications to assess. The study by Hood et al., further found that most diabetes applications target patients broadly and not by the type of diabetes they have or other demographic factors. Targeting the applications by more specific details could be an important consideration for application designers to consider.

The number of patients that were using an application for a study in the management of epilepsy had decreased significantly at the end of the study (Choi et al., 2021). This could be an indicator of application use issues and a further indicator that mHealth use should be studied further.

Most studies in the management of chronic illnesses found that mHealth could have a positive impact on the management of these diseases. A literature review aimed at assessing the possible impact of mHealth in encouraging women to have their cervical cancer screening found that SMS interventions are useful for short term interventions but factors such as the SMS structure, whether the SMSes will be combined with

phone calls or other communication types may be more beneficial for long term interventions (Bhochhibhoya et al., 2021). This was further supported by another study which was aimed at assessing the impact of mobile in the management of cervical cancer, the study found that short, clear and concise SMSes are more impactful in encouraging women to go for their cervical cancer screenings and could be a potential adoption hinderance if not taken into consideration (Moodley et al., 2019). This brings the spotlight into taking technology characteristics under consideration when designing an mHealth application. A literature review conducted to analyse commonly used mHealth applications found that SMS interventions for health promotion and rising health awareness were the most commonly used types of mHealth applications in low income countries (Abaza & Marschollek, 2017).

In South Africa, most studies related to mHealth have focused on HIV care, information on physical activity, child health and gender based violence and other social issues (Mogoba et al., 2019). The topic trends in mHealth studies in South Africa are related to some of the social issues that burden the country. An investment in understanding how mHealth can be used to manage or educate on some of these social issues would be a worthy and positive investment. Mobile phones have been identified as having the capabilities to improve access to health and delivery in poor remote South Africa (Anstey Watkins et al., 2018). This support for mobile phones impact could further support the possibilities of tapping into understanding the impact that mHealth applications could have in the South African health sector.

Most studies related to mHealth innovations indicate that scalability is a major challenge. A study which aimed to summarize the challenges related to moving an mHealth pilot study to full-scale adoption found that one of the challenges that must be overcome is that mHealth must be built with usability in mind (Wallis et al., 2017). The usability traits that should be considered include the user's age, technological capabilities and role in relation to the application (Wallis et al., 2017). A study on the prospects and challenges of mHealth in developing countries, which South Africa is part of, found that in order to enjoy the benefits that come with mHealth interventions countries must design and develop strategies that overcome the challenges that mHealth interventions face at full implementation (Nsor-Anabiah et al., 2019). One of the two challenges identified as a barrier into the scalability of mHealth interventions in the developing world is developing applications which consider socio economic factors such as acceptance by users, technology awareness and other human factors (Istepanian et al., 2020). A study that had the purpose of analysing mHealth interventions in developing countries found that most mHealth interventions do not move beyond the pilot phase and further suggested that national health policies

should include scalability and sustainability as important success measures for an mHealth intervention (Latif et al., 2017).

The common theme is that interventions do not reach full scale and that usability should be an important consideration when building mHealth applications. This offers an opportunity to further explore factors that could impact the adoption and use of these mHealth applications.

2.2 mHealth Technology in South Africa

The World health Organization (WHO) states that health related indicators in the Africa region continue to show slow progress despite efforts to decrease mortality and to slow down the impact of infectious diseases and that socioeconomic and epidemiological issues related to migration and climate change contribute to the disease burden in Africa (WHO, 2011). Furthermore, the challenges highlighted by WHO require new technological innovations emanating from the Africa region itself and even though this is a great opportunity, innovators still face challenges with scaling up their innovations (WHO, 2011). Scaling up high impact community based mHealth interventions is one of the agenda items mentioned in the National Digital health strategy for South Africa for the period 2019 -2024 (National Department of Health [NDoH], 2019). This is a good indicator that scaling up mHealth application is part of the government's priorities. MomConnect, a nationwide mHealth system designed to equip South African pregnant women with pregnancy health related information with the aim of minimizing infant and maternal mortality has become the blue print for demonstrating that large scale digital health systems are feasible not just in South Africa but world wide (Mehl et al., 2018). A study which aimed to better understand the different approaches that can be taken to scale up a technological innovation noted that South Africa has an advantage in that there is a supportive policy which supports the absorption of innovations and also skilled partners, a high penetration of mobile phones and acceptable levels of technology literacy (Swartz et al., 2021). This shows that South Africa can scale up mHealth interventions successfully. Another review of mHealth interventions in developing countries suggested that there is a necessity for further research to focus on how countries can be assisted to reach their mHealth goals and increase the acceptance of mHealth interventions as a way to improve healthcare (Kruse et al., 2019). The success of MomConnect, supportive policy, high phone literacy and an increase in phone use are just some of the reasons that indicate that a model to assess the use and acceptance of mHealth technology in South Africa would be beneficial and is worth exploring further.

A study aimed at exploring the impact of mHealth technology to report adverse events found that in order to understand the impact of mHealth interventions, factors that motivate further use should be researched (Chaiyachati et al., 2013). A study which aimed to scope the mHealth landscape in South Africa found that most of the mHealth initiatives are donor funded and no business model existed for implementation beyond the funding period, another scaling challenge (Botha & Booi, 2016). The study further found that most mHealth initiatives in South Africa are targeted towards the general public (individual users) and focus on drug adherence, HIV drugs distribution and pregnancy related information (Botha & Booi, 2016). A review on mHealth use in Sub Saharan Africa found a similar theme, which is that beneficiaries of mHealth interventions are HIV/AIDs patients, pregnant women, breast feeding mothers, children and general adults (Bervell & Al-Samarraie, 2019). A pilot study for an application called Masivukeni, an application meant to assist with Anti-retroviral therapy (ART) readiness counselling raised questions about the feasibility of scaling (McCreesh-Toselli et al., 2021). These studies and their attention on scalability or moving beyond the pilot phase indicate that scalability is still a serious challenge in the adoption and use of mHealth applications.

There have been several studies conducted in South Africa to assess the possibility of mHealth being used support the health care services. A few are summarized in the next paragraphs. A study conducted in Zimbabwe, South Africa and Malawi found that SMS reminders improved the numbers of self-supported HIV testing (Govender et al., 2019). Another study related to SMS reminders found medication adherence support for hypertension delivered on a patient's phone to be helpful and acceptable (Leon et al., 2015). A study which focused on piloting MHealth to support HIV self-testing services, found that the application was suitable for uploading the HIV results emanating from self-testing (Gous et al., 2020). In 2019, there was a study conducted to determine the tasks that could be automated using an mHealth solution to deliver home based HIV testing and counselling with the aim of improving linkage to care and adherence to ART medication (Comulada et al., 2019). A study which was aimed at studying out the effectiveness of a mHealth for diabetes found that patients preferred mHealth as a method of seeking medical treatment (Petersen et al., 2020). A study aimed at investigating the use of WhatsApp as an mHealth tool to support fracture management by doctors who are not orthopaedic doctors revealed that the use of WhatsApp decreased the delay to care and also reduced unnecessary referrals to already overburdened facilities and also empowered doctors who are not orthopaedic doctors to manage fractures (Kauta et al., 2020). These

few mentioned studies just demonstrate the power of mHealth and its impact on how people can receive health care services in an improved way.

Most studies on mHealth inventions in South Africa were on the management of HIV/AIDS and most of the studies reviewed indicate a positive possibility of how mHealth applications can impact the South African health sector.

2.3 mHealth Acceptance and Use

A study aimed at understanding the determinants of mHealth adoption in developing countries, found that Performance Expectancy (PE) and Effort Expectancy (EE) are drivers in a user's intention to use and adopt an mHealth application (Alaiad et al., 2019). Performance Expectancy relates to the user's idea that a technological innovation will improve how they manage their health and as a result improve their lives. Effort Expectancy relates to how easy they think the technology is to use and whether it is convincement for completing the tasks that it is meant to automate. The study further indicated that when mHealth designers are building applications with PE in mind, they should consider applications that give users greater freedom in terms of managing their health and consider the amount of time it would take to use the mHealth application (Alaiad et al., 2019). Another technology characteristic the study suggested is building the mHealth application user interface in such a way that users can complete their tasks correctly and in a manner that does not take an unnecessary amount of time (Alaiad et al., 2019). The study also suggested that technology builders should consider the skills and demographics of the users that they are building the mHealth technology for if they want to consider the Effort Expectancy behavioural construct. The study findings are similar to a study which aimed to determine the constructs that can improve the acceptance and use of mHealth applications in that performance and effort expectancy have a significant impact on the acceptance and use of mHealth applications (Nunes et al., 2019). It is worth noting that Effort Expectancy only had a significant impact on users who were male. A study aimed at studying the factors that influence the behavioural intention to use physical activity mHealth applications in South Africa also found that Performance Expectancy, Effort Expectancy and Social Influence (SI) were dominant factors (Ndayizigamiye et al., 2020). The findings in the above studies just indicate that there is a link between the behavioural constructs that influence the user acceptance and use of mHealth and the technology characteristics. This brings into the spotlight the idea that studying a technological innovation's intended users and mapping their behaviour to the characteristics of the technology has the potential to influence the user acceptance and use of the technology.

A study aimed at understanding physicians' views of how mHealth can impact the quality of health found that ease of use and timeliness are important in influencing physicians to view mHealth positively (O'Connor et al., 2020a). A study conducted with the purpose of understanding the acceptance of an mHealth system which was piloted in one of the districts in Ghana with the purpose of supporting children's healthcare found that all the four constructs of UTAUT had an influence on acceptance and use (Brinkel et al., 2017). The level which individuals believe that the system will help them gain competitive advance, ease of use, organizational and technical infrastructure and social factors such as education had an impact o the intention to use the mHealth system (Brinkel et al., 2017). One study which deviates from most studies analysed found that trust was a motivator in the adoption of mHealth and cited that users struggle with adopting mHealth applications because they do not believe that mHealth applications can protect their personal information (Barutçu, 2018). Trust could be a critical decider for the intention to use and accept mHealth applications since some applications will be collecting personal health information.

A systematic review aimed at analysing studies related to the use and acceptance of mHealth found that perceived usefulness and perceived ease of had the most impact on the behavioural intention to use an mHealth application (Kaium et al., 2019). Another review related to analysing the factors that could increase or decrease mHealth adoption also found perceived ease as a major contributor to the adoption (Agbenyo, 2019). A study into the adoption of mHealth by the elderly found that Performance Expectancy and Effort Expectancy did not have an impact in the adoption of mHealth, this finding was different from most studies (Palas et al., 2022). It found that Social Influence had an impact on the adoption and tied it to the cultural influence of family on health decisions. The common theme in most of the studies identified is that /Performance Expectancy and Effort Expectancy have a significant impact on the intention to use and accept mHealth. Users want to use technology that is easy to use and technology which will help perform the task that the technology aims to automate. This also then directly impacts the technology characteristics of the technology; technology must be easy to use and should add value to the lives of its users.

2.4 Theoretical Frameworks

2.4.1 The Unified Theory of Technology Acceptance and Use of Technology (UTAUT)

The UTAUT emanated from the notion that researchers were confronted with multiple theories and would often pick and choose the constructs from their favourite models, so a model that was directed towards a unified view of acceptance needed to be developed (Venkatesh et al., 2003). It was developed using common concepts and similar characteristics from eight different theories related to the use and acceptance of technology (Venkatesh et al., 2003). The UTAUT uses four variables that are predictors for adoption, Performance Expectancy, Effort Expectancy and social influence and another variable which has a direct impact on actual usage, Facilitating Conditions (FC) (Arfi et al., 2021). Age, gender, experience and voluntariness are moderating factors of the relationships in the model (Arfi et al., 2021). Performance expectancy refers to the belief that individuals who use the system will perform higher (Ayaz & Yanartaş, 2020). It is the degree which an individual believes that using the system will help them achieve a higher job performance (Alam et al., 2021). Consumers of a certain technology tend to be motivated to use and accept that technology if they believe that it will add value and make their daily lives easier (Alam et al., 2021). Effort Expectancy refers to the level at which it is convenient to use the system (Ayaz & Yanartaş, 2020). Social influence refers to the level which an individual whom the user holds in high regards deems the system as important (Ayaz & Yanartaş, 2020). It is related to the influence that the thoughts and activities of peers has on the behaviour of the individual (Alam et al., 2021). Facilitating condition is the degree which a consumer believes there is support and infrastructure to support the use the technology.

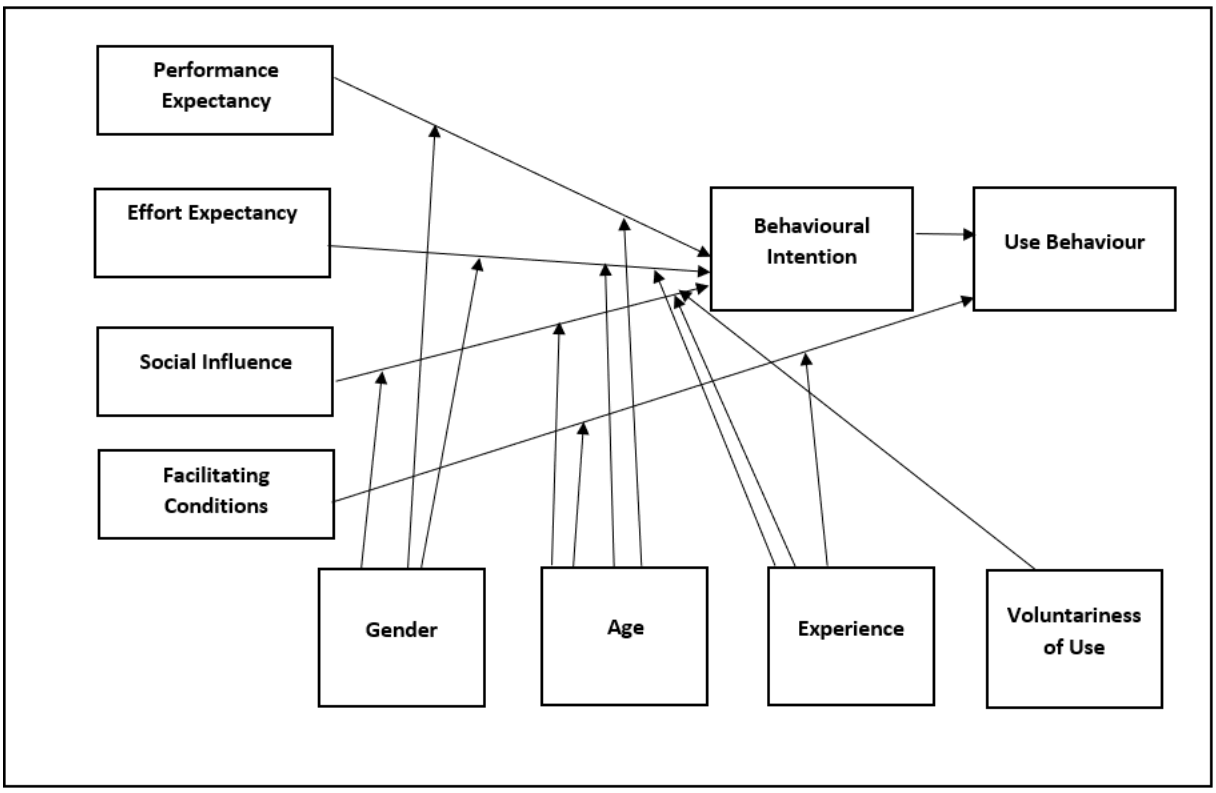


Figure 1: UTAUT Model (Venkatesh et al., 2003, p. 447)

The framework has been used to analyse the use and acceptance of various technological innovations at the individual level and at the organizational levels through studying out the patterns of individuals in the specific organization. Some use the extended version of the UTAUT, which is the UTAUT2. UTAUT2 was introduced by the same researchers who initially developed UTAUT. They extended the model by adding additional constructs and relationships to tailor it to a consumer use context (Venkatesh et al., 2012). UTAUT was used in the study. The UTAUT theory has been used to study the acceptance and use of mHealth from a patient's perspective in Bangladesh (Alam et al., 2021). The study found that the model is a good model to use for the prediction of a young generation's intention to use mHealth technology and was also aligned with other gender roles studies which found females to have higher technology anxiety and lower self-expectancy when dealing with new technological innovations (Alam et al., 2021).

It has also been used to study the reason that people use location based applications for emergency situations which found that Effort Expectancy and facilitating conditions do not have a significant impact on the behavioural intention to use the technology, which means that users did not take the complexity of the technology and the level of support available for the technology into consideration when using the technology (Ayuning Budi et al., 2021). There have also been two studies where the model was used to

understand the use and acceptance of internet of things technology. The one study found that Performance Expectancy played a pivotal role in the user's usage of the technology and also that Effort Expectancy also had a positive impact on usage behaviour (Ronaghi & Forouharfar, 2020). Another study which used UTAUT to better understand the use and acceptance of internet of things technology similarly found that Performance Expectancy and Effort Expectancy have a positive impact on usage of the technology, if the technology improves a user's daily life and is easy to use then it is likely to be adopted and used by users (Isaac et al., 2019). It is also worth noting that UTAUT was used in conjunction with Task-technology fit in the second study mentioned. Since age is also mentioned as a moderating factor in the relationships that exists within the model, other studies have focused on the acceptance and use by users from a particular age group. For instance, it was used to better understand the use and acceptance of information technology by older adults (Macedo, 2017). The study found that intention to use is a high determining factor in the actual usage of the technology and that older adult's usage behaviour is directly proportional to the value that they think the technology adds to their lives (Macedo, 2017, p. 945). The study also found that effort efficacy and facilitating conditions play an important role in the acceptance of technology by older adults, and that technology should not be complex and that a supportive environment for the use of the technology should exist (Macedo, 2017). A study on the acceptance of an electronic document management system also re-enforced the fact that Performance Expectancy was an important determinant in the behavioural intention to use (Ayaz & Yanartaş, 2020). UTAUT has also been used to study the acceptance of telehealth services (Cimperman et al., 2016) and also patients' intention to use an online portal to post an emergency department's waiting times (Jewer, 2018). Other health related studies include a study which investigated nurses' intention to use an Electronic Patient Record system (Maillet et al., 2015) and also to study the factors that influence the acceptance and use of an Electronic Record System in a context where there are limited resources (Shiferaw & Mehari, 2019). The study from the limited resource setting found that those developing health systems in Sub-Saharan Africa should focus on improving the attitudes, efficacy and awareness for health care professionals for the successful acceptance and use of those systems (Shiferaw & Mehari, 2019). A study which aimed to investigate the factors that influence a physician's adoption of an Electronic Health Record (EHR) system in Bangladesh found that facilitating conditions play a pivotal role in the adoption of an electronic record system, so the availability of infrastructural support is important to physicians (Hossain et al., 2018). This study however found an insignificant relationship between Effort Expectancy, Performance Expectancy and the physician's behavioural intention to use the EHR system (Hossain et al., 2018). Another study which aimed to understand the adoption of a mobile online hospital and their use by patients in West

China found that Performance Expectancy, Effort Expectancy, and facilitating conditions were the main factors that were found to motivate patients to use the online hospital (Addotey-Delove et al., 2023). A similar study related to the adoption of mobile technology into the health system in Bangladesh also found Effort Expectancy and facilitating conditions to be significant in the adoption of the technology (M. Alam et al., 2019). Another common denominator in these studies related to health is facilitating conditions, users will use a technology if there is an enabling environment and infrastructure.

UTAUT has been used in several studies related to the adoption of technology in the health sector, thus making it a suitable model for the study.

2.4.2 Task-Technology Fit (TTF)

The TTF model emanated from two areas of research that complement each other, from user attitude as a predictor of system usage and task-technology fit as a predictor of performance (Goodhue & Thompson, 1995). It extends beyond the original proposed model by (DeLone & McLean, 1992) which states that both system usage and attitude related to the technology lead to individual user performance impact (Goodhue & Thompson, 1995). The TTF model focuses on the role that task-technology fit plays on performance impact, this is noteworthy since task-technology fit was a missing construct in many various models or was just hinted at and not explained explicitly (Goodhue & Thompson, 1995). The task characteristics in the model refer to the individual user's actions and the technology characteristics refer to the technology that the individuals use to perform their tasks (Yang et al., 2013). Another definition for TTF is a way in which the technological innovation's characteristics meet the task requirements of a user in such a way that performance is increased (Shahbaz et al., 2021a). The model essentially suggests that users will adopt a technological innovation based on how it will improve the efficiency of their daily tasks (Oliveira et al., 2014). It further suggests that the user's performance while using the technological innovation will be determined by how well the technology fits the user's task requirement (Park et al., 2015).

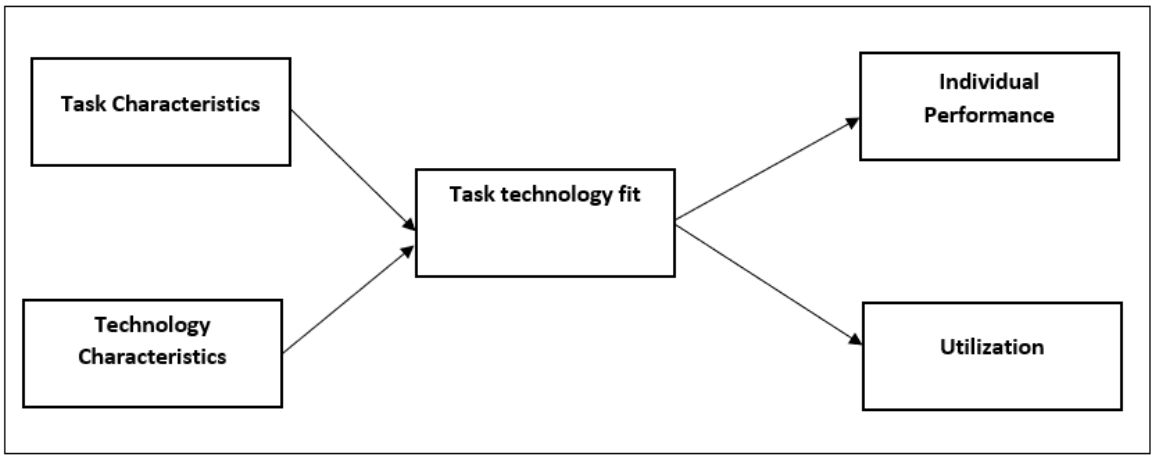


Figure 2: TTF Model (Goodhue & Thompson, 1995)

Figure 2 is a pictorial view of the model. The figure demonstrates that task and technology characteristics affect the Task Technology Fit which lead to user utilization of the technological innovation and also individual performance of the user (Zhou et al., 2010a).

There have been several studies which used TTF in the health sector. A study on the adoption factors of mobile technology for frontline patient care using TTF and human drivers found that understanding fit to be an important consideration when building a health information system (Junglas et al., 2009). One study which was intended to study the adoption of a personal health record system by patients who have chronic illnesses used TTF together with the Intervention Theory and the Protection Motivation Theory. The study found that task and technology characteristics play an important role in the Task Technology Fit and can influence adoption (Laugesen & Hassanein, 2017). Another study which was meant to better understand the adoption pattern of an electronic health record (EHR) by health care providers in the United States of America (USA) found that designers of EHR systems should take the characteristics of the organization into consideration when designing EHR system so as to ensure fit and in turn proving that technology and task characteristics are significant in the adoption of a EHR system (Gan, 2015). TTF in partnership with the UTAUT model has been used to study the acceptance of wearable devices in the health care sector. The task and technology characteristics were found to have an impact on TTF which further impact the decision to use and accept the wearable devices, the authors noted that this was different to other results on the adoption of wearable devices in the health sector (Wang et al., 2020a).

TTF is a model that is just above 25 years old and has been used since its inception and is still being used in recent studies. The results in most of the studies are consistent in that they found task and technology

characteristics as an important determinant of requirements gathering when building a new technology. The model is also a good partner when matched with other theories as indicated by the studies listed above. TTF has a solid theoretical background. The reasons mentioned make TTF a suitable model to also use in the current study.

The proposed model uses a combination of the UTAUT and the TTF models to derive a model for the factors that affect the use and acceptance of mHealth technology in the health sector in South Africa. Task characteristics and technology characteristics as determinants of Task Technology Fit which will also affect user adoption.

2.5 Model of the study

2.5.1 Task Characteristics

The task characteristics of a technology can refer to actions that individual users put in as input for outputs that meet their information needs (Tam & Oliveira, 2016). A task can vary in how routine it is, the amount of time it takes to execute and whether is dependent on other tasks or not. The theory is that the more complex a technology is or the less functionalities an information technology offers, user's positive view of the technology will decrease (Tam & Oliveira, 2016). This leads to the first hypothesis below:

H1: Task characteristics of mHealth positively affect the Task Technology Fit.

2.5.2 Technology Characteristics

Technology characteristics refers to the technological tool used by individual users to carry out their tasks (Tam & Oliveira, 2016). Attributes such as design and ease of use can affect how users view the technological innovation and also usage of the technology (Tam & Oliveira, 2016). Technology design can also affects how and how much a technology will be used, so a poor technology design or design choices not fitting the task will be overlooked for other technology (Tam & Oliveira, 2016). If a technology is designed with user's requirements in mind, it creates a perception or idea that the technology will improve the user's work activities or daily activities (Shahbaz et al., 2021b). Technology is likely to be adopted if it sufficiently supports the tasks it must perform (O'Connor et al., 2020b). Therefore:

H2: Technology fit of mHealth positively affects the Task Technology Fit.

2.5.3 Task Technology Fit

TTF refers to a fit between task and technology characteristics which will influence the use and task performance of individual users technology (Tam & Oliveira, 2016). If the tasks that a technology supports increase and become too complex for a technology to support, then the TTF decreases. If the technology functions increase to meet the task requirements, then TTF increases. The task characteristics refers to the use of mHealth applications to improve health (Yu et al., 2019). Therefore:

H3: Task Technology Fit has a positive influence on the use of mHealth.

2.5.4 Performance expectancy

Performance Expectancy refers to the positive impact that using a technology will have on users performing certain tasks (Wang et al., 2020a). It is a primary determinant in the use of technology (Wang et al., 2020). Therefore:

H4: Performance Expectancy positively affects user adoption of mHealth.

2.5.5 Effort Expectancy

Effort Expectancy refers to the degree which the user perceives the technology to be easy to use. If users believe that a technological innovation is easy to use then there is a higher change of them accepting the technological innovation (Wang et al., 2020a). Therefore:

H5a: Effort Expectancy positively affects user adoption of mHealth.

H5b: Effort Expectancy positively affects Performance Expectancy.

2.5.6 Facilitating Conditions

Facilitating conditions refers to the degree which an induvial user believes organizational and technology infrastructure are available for the use of the technological innovation (Wang et al., 2020). Infrastructure such as internet bandwidth or ability for use the application offline can encourage technology use (Wan et al., 2020). These conditions facilitate the skills, knowledge, and support to use the technology (Wang et al., 2020). Therefore:

H6: Facilitating Conditions positively affect user adoption of mHealth technology.

2.5.7 Construct relationship among UTAUT and TTF

Previous studies have found that Task-Technology Fit has a positive impact on Performance Expectancy, which means that users will only adopt mHealth if the functionalities of the mHealth application meet

their health management tasks (H. Wang et al., 2020). Many studies have also reported that the attributes of mHealth may reduce the effort to monitor health related issues. Therefore:

H7: Task Technology Fit of mHealth has a positive relationship with Performance Expectancy.

H8: Technology characteristics of mHealth have a positive relationship with Effort Expectancy.

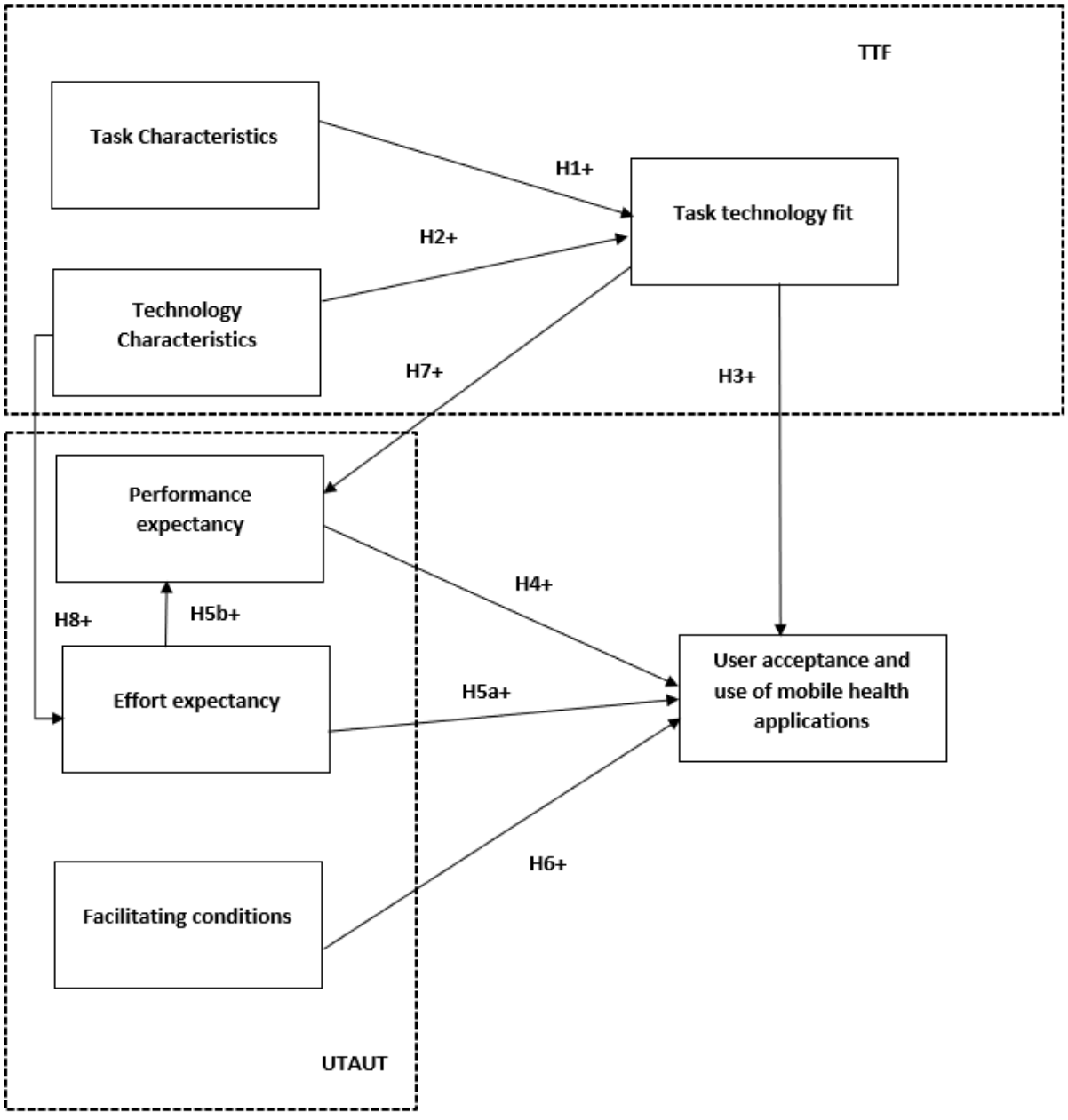


Figure 3: Proposed conceptual framework.

Figure 3 is the proposed conceptual framework for the acceptance and usage of mHealth technology in the health sector in South Africa at the individual level. The figure demonstrates the possible constructs that can have a significant impact on the user adoption of mHealth through the different hypotheses. The independent variables from the TTF theory are task characteristics and technology characteristics and from the UTAUT theory, the independent variables are Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. The independent variable from the combined model is the Task Technology Fit. The dependant variable is the user adoption of mHealth. Social Influence was not included as a construct as its not of interest for this study. Table 1 contains a summary of the hypotheses which were derived from the TTF and UTAUT theoretical framework.

Table 1: Summary of Hypotheses

Construct	**Hypothesis Number & Description**	**References**
Task Characteristics	**H1**: Task characteristics positively affects the Task Technology Fit	(Tam & Oliveira, 2016, p. 237)
Technology Characteristics	**H2**: Technology fit of mHealth positively affects the Task Technology Fit	(Tam & Oliveira, 2016, p. 237) (Shahbaz et al., 2021b, p. 4)
Task Technology Fit	**H3:** Task Technology Fit has a positive influence on the use of mHealth	(Tam & Oliveira, 2016, p. 237).
Performance Expectancy	**H4:** Performance Expectancy positively affects user adoption of mHealth	(Wang et al., 2020a, p. 4)
Effort Expectancy	**H5a**: Effort Expectancy positively affects user adoption of mHealth **H5b**: Effort Expectancy positively affects Performance Expectancy	(Wang et al., 2020a, p. 4)

Facilitating Conditions	**H6**: Facilitating Conditions positively affects user adoption of mHealth technology	(H. Wang et al., 2020, p. 2)
TTF and UTAUT	**H7**: Task Technology Fit of mHealth has a positive relationship with Performance Expectancy. **H8**: Technology characteristics of mHealth have a positive relationship with Effort Expectancy	(H. Wang et al., 2020, p. 3)

CHAPTER 3: RESEARCH METHODOLOGY

3.2 Research Paradigm and Approach

The research paradigm used in the study is the positivist paradigm. The positivist paradigm can be described as a method for combining deductive logic with empirical observations of individual behaviour to try formulate rules that are based on a probability in order to come up with some pattern or generalization for human behaviour (Antwi & Hamza, 2015, p. 219). Researchers who work under the positivist paradigm work in quantitative terms to explain how items interact, how certain events are shaped and the causes of certain outcomes (Antwi & Hamza, 2015). Positivist researchers believe that reality stays the same and is not subjective to circumstances, and that it can be studied objectively (Rahi, 2017). Oates (Oates, 2005) states that positivism research has two fundamental assumptions or theoretical roots. The first assumption is that the world is ordered and regular, not just a haphazard occurrence (Oates, 2005). The second assumption is that the world can be analysed objectively without any emotions or feelings attached (Oates, 2005). Positivism focuses on finding out phenomena in the world without our personal preferences attached but in an objective manner (Oates, 2005). Researchers that use the positivism approach believe that we can understand the world through experiments and observation, it is also called the scientific or empirical method (Rahi, 2017). Positivism removes the researcher from what is being researched, numeric measurement is used with the aim of generating acceptable knowledge (Wahyuni, 2012). Numeric measurement was used for in the study, that is why the positivist research paradigm was appropriate for the study. The Positivist research is rooted in numeric and quantifiable data, so the research approach used in the study is the quantitative research approach. This is the scientific approach and focuses on collecting data from a sample that represents the population and the analysing the data but ignoring an individual's feelings and emotions (Rahi, 2017). Quantitative researchers consider it very important to state their hypotheses and to test those hypotheses with empirical evidence to see if the hypotheses are supported or not (Antwi & Hamza, 2015). Positivism was selected as suitable for the study because the TTF and UTAUT frameworks were used to test the relationship between the dependant and independent variables and testing the hypotheses to establish the impact of the variables on the user adoption of mHealth technology. Furthermore, each hypothesis was tested using various statistical methods to test whether they are true or not, which also makes the paradigm suitable since.

Table 2 shows the key characteristics of the quantitative research approach and demonstrates even further why it was the selected research approach for the proposed study.

Table 2: Key Attributes of Quantitative Research (Basias & Pollalis, 2018, p. 93)

Key Attribute	Description
Examines	
Interpretation	The quantitative research method uses statistics and data analyses to interpret large amounts of data
Usually Selected when	- When it is necessary to analyse a large amount of data to verify or prove hypotheses - The research can be conducted using simple questionnaires with short answers that can be easily compared. -
Data attribute	Numeric data that can be collected using questionnaires
Advantages	- The result is quantifiable and therefore considered objective. - Quantitative data makes it easier to highlight changes and differences. - It makes it easier to compare numeric data. - Facilitates the development of valuation indicators

3.2 Research Design

3.2.1 Types of research designs

The research design refers to the way that the researcher chooses to organize the different components of the research paper in a logical and coherent way such that the research problem is addressed adequately (Kumar, 2014). The research design allows us to translate our collected research into valuable and usable information (Nardi, 2018). It is a comprehensive plan for data collection in an empirical study and has the purpose of answering research questions or testing hypotheses (Bhattacherjee, 2012). It contains an overview of how data will be collected, measured and then analysed (Mishra & Alok, 2017). This is where the researcher communicates the plan that they will undertake to complete their study and describes the measures that they will take to collect valid, objective, and accurate data. There are many different types of research designs which a researcher can choose from depending on the research question they wish to address (Walliman, 2017). The choice depends on the type of problem that the researcher wishes to resolve (Walliman, 2017). The research design that was used in the study is the

explanatory design type. It has the purpose of explaining observed phenomena and behaviour (Bhattacherjee, 2012). Explanatory research looks at phenomena through casual relationships (Rahi, 2017). It explains why things happen the way they do (Kumar, 2014). The main aspect is to make it clear as to why and how there is a relationship between variables (Kumar, 2014). The advantages of explanatory research can be summarized as follows:

- They play a role in identifying the norms behind a wide range of issues (cscscholarship, 2018)
- It is easy to replicate an explanatory study (cscscholarship, 2018)
- They are associated with a high level of internal validity since there is an organized way of selecting the study subjects (cscscholarship, 2018)

It was the most appropriate design for the study because it looks at cause and effect relationships, our research was aimed at summarizing the factors that affect the use and acceptance of mHealth applications by individuals in the South African health sector. The purpose of further understanding these factors was so that barriers to mHealth adoption could be mitigated and aiming to understand why sometimes there is adoption of mHealth and sometimes there is not. The reasons mentioned resonated with the core goal of explanatory research.

3.2.2 Survey Research

The survey method is a systematic way of collecting data about people, thoughts, behaviour and their preferences in a standardized and systematic way using questionnaires or interviews (Bhattacherjee, 2012). Its main purpose is to gain a better understanding about a specific group or a sample representing a larger population (Jonker & Pennink, 2010). Surveys are mostly used to study individuals but can be used to study other groups such as organizations (Bhattacherjee, 2012). Though in such a case, a key informant for that group is used. In the case of the current study, the key informants are individual users of mHealth in the South African health sector. Surveys have many advantages when compared to other research methods, the first one is that they are a reliable way of measuring data that cannot be observed (Bhattacherjee, 2012). The second advantage is that they are an easy method for selecting data remotely (Bhattacherjee, 2012). Thirdly, they are seen as a convenient method of data collection by respondents since they can respond in their own time and space (Bhattacherjee, 2012). The fourth advantage is that the survey method is economical in terms of the researcher's resources such as time, effort and money (Bhattacherjee, 2012). The study used the survey method because it is more suitable when trying to

understand a group of individuals. The study also used a sample to represent a larger population, Gauteng province was used to generalize mHealth adoption factors related to South Africa. Thirdly the questionnaire was disseminated remotely another core positive of the survey method that was considered when making the decision to use the survey method. Lastly the survey method is also excellent for measuring people's perceptions or beliefs about a specific topic.

3.3 Data Collection Methods

Data collection is defined as the process of gathering information about a specific research matter in order to answer research questions, test hypotheses or evaluate outcomes (Kabir, 2016) . The reason that data was collected in the study was to test the hypotheses stated in Section 2.5 of this report.

3.3.1 Operationalization/ Measurement and Instrument Construction

Operationalization is the process of designing precise measurements for abstract items (Bhattacherjee, 2012). The first step is to define an operational definition for the constructs that the researcher is interested in (Bhattacherjee, 2012). The constructs were developed using various adoption literature. A 7-point numerical scale survey was adopted with 7 indicating Strongly Agree and 1 indicating Strongly Disagree. This is consistent with other similar studies (Zhou et al., 2010b). The constructs are defined as per Table 3.

Table 3: Measurement Constructs

Constructs and Items	**Source**
Task Characteristics (TAC) - I need to access my health-related information anytime anywhere. - I need to acquire my health-related information anywhere. - I need to know my health-related information anywhere.	(Zhou et al., 2010b)
Technology Characteristics (TEC) - MHealth provide ubiquitous service. - MHealth provide real time services. - MHealth provide services where my privacy is protected.	(Zhou et al., 2010b)
Task technology fit (TTF) - The functions in mHealth are enough for the management of my health. - The functions in mHealth are appropriate for the management of my health. - Generally, the functions of the mHealth technology I use meet my needs.	(Wang et al., 2020b)
Performance expectancy (PEE)	(Zhou et al., 2010b)

- I feel mHealth is useful in collecting health related information. - Using mHealth enables me to obtain health related information quickly. - Using mHealth provides me with the information that I need.	
Effort Expectancy (EPE) - I can quickly and easily use a new technological tool. - I find that using mHealth that I use easy. - I think learning to operate new technology is easy for me. - My interaction with the mHealth that I use is clear and understandable.	(Wang et al., 2020b) (Zhou et al., 2010b)
Facilitating Conditions (FAC) - I have the necessary resources to use mHealth that I use. - I have the necessary knowledge to use the mHealth that I use. - Support is available if I struggle with a function of the mHealth that I use.	(Wang et al., 2020b)
User Adoption of mHealth (UAU) - I predict that I would use a mHealth to manage my health-related information. - I can develop a habit of using a health-related mobile application. - I foresee myself using a mHealth to manage health related issues	(Wang et al., 2020b)

The survey was created using Google forms, see Appendix A for the final research instrument.

3.3.2 Sampling and Respondents

Sampling is a statistical process which involves selecting a subset from the population of interest such that observations and statistical inferences can be made about the population (Bhattacherjee, 2012). The first step is defining the target population (Bhattacherjee, 2012) . The population for the study was users who use mHealth in South Africa. The population categorisation for the study were adults (anyone older than 18) who own a smart phone and those who were users and are potential users of mHealth and are based in the province of Gauteng, South Africa, similar to other studies (Wang et al., 2020b). The second step in the sampling process is to select the sampling frame. This can be in the form of a contact list that is accessible (Bhattacherjee, 2012). Once the sampling frame was determined, the sample size was determined using Cochran's Sample Size Formula, this formula as used because it is ideal for determining the sample size for large populations (Nanjundeswaraswamy & Divakara, 2021).

The last step in the sampling process is choosing the sample using a selected sampling method (Bhattacherjee, 2012). The convenience sampling method was used for the research. Convenience

sampling collects data from whoever is willing to take part in the study and is conveniently accessible (Scholtz, 2021). It was chosen to avoid high research costs and because it makes data collection easy.

3.3.3 Pilot testing

Pilot testing is an important part of the research process, it can assist with the detection of research design issues or issues with the research instrument (Bhattacherjee, 2012). It ensures that the measurement instrument is a reliable and valid source of measure (Bhattacherjee, 2012). The instrument was piloted to 10 respondents before being disseminated to the sample for data collection. The 10 respondents were not part of the final study results. No major updates were made after the pilot except for suggestions on the presentation of the questionnaire as some respondents in the pilot phase struggled to navigate the questionnaire.

3.3.4 Questionnaire administration

Once the pilot test was done, the data collection instrument link was administered online via e-mail and link sharing on social media. This was done through WhatsApp contacts and LinkedIn in contacts. The survey was shared between December 2021 and April 2022. The questionnaire was then turned off to stop accepting responses.

3.4 Data Analysis Strategy

Internal consistency was tested. This is a measure of consistency amongst different items of the same construct (Bhattacherjee, 2012). This is a measure of how likely respondents rate items of a multi item construct (Bhattacherjee, 2012). Internal consistency was measured using Cronbach's alpha to estimate this consistency. The second measure for consideration is construct validity. It measures whether the proposed construct is a good measure of the topic of interest (Bhattacherjee, 2012). Correlational and factor analysis was used for this measure. Face validity refers to whether a measurement seems to be a good measure of a construct. The analysis also analysed for content validity, this is an indication of whether scale items match the content domain of a construct. There are two types of statistics for analysing data, descriptive and inferential statistics. Descriptive statistics aggregate data that are grouped to examine typical values and the characteristics of the data whereas inferential statistics make conclusions about a group of data and can draw conclusions on a population based on a sample (Guetterman, 2019). The difference between the two is that inferential statistics goes beyond just describing the data (Guetterman, 2019). A combination of inferential statistics and descriptive statistics was used to analyse the data collected during the study. A comprehensive summary of the different findings and tests conducted on the data is available in Chapter 4 of this report.

3.5 Ethical Considerations

Ethics refers to the conforming of rules or regulations set by a specific group or a professional body (Bhattacherjee, 2012). Participants should be made aware that their participation is voluntary and that they can withdraw at any time (Bhattacherjee, 2012). This was stipulated in the e-mail and social media link sharing when the questionnaire was administered. Another consideration considered was to ensure confidentiality of participants (Bhattacherjee, 2012). This was done though ensuring that the questionnaire does not collect self-identifying data. Disclosure of who is doing the study, what the study is about, why they are doing the study, and the purpose of the study was shared to assist the participants with deciding on whether they want to part take in the study or not. It is also important to ensure that all results are reported, no matter what the outcome is (Bhattacherjee, 2012). This was adhered to for this study. The last consideration was any recommendations made by the Wits School of Business Sciences' ethics committee under the approval for protocol CBUSE1963, see Appendix B for more details.

CHAPTER 4: PRESENTATION OF RESULTS

4.1 Data Screening

The purpose of this Chapter is to present the findings of the study. Both descriptive and inferential statistical results are presented in the chapter.

A total of 107 participants voluntarily took part in the study. All participants gave consent confirming the below:

1. My participation in the survey is solely voluntary.

2. It is my right to withdraw from the survey at any given stage.

3. Only people who live in Gauteng, and are 18 years and above, can respond to the questionnaire.

Only 70 of the participants were used as part of the analysis. Those excluded were missing responses in some questions due to the skip logic. Those excluded had answered 'No' to having used an mHealth application. The implication for the study was that only responses for those who responded to have used mHealth were used. The data set was imported into IBM SPSS for analysis.

4.1.1 Missing Data

All the included responses in the survey were correctly completed in accordance with the skip logic in the survey. This is due to the questionnaire being designed in such a way that participants only respond to questions that were relevant to them. Another factor which led to there no being missing data is that all the questions were marked as required in the electronic survey shared and participants could not proceed to the next question before providing a response for the previous question.

4.2 Demographic Analysis

The sample comprised of 41 females and 28 males, which translates to 58.6% and 40% respectively. 1.4% of the respondents did not provide their gender.

Table 4: Gender Statistics

Gender	Frequency	Percent	Valid Percent	Cumulative Percent
Unspecified	1	1.4	1.4	1.4
Female	41	58.6	58.6	60.0
Male	28	40.0	40.0	100.0
Total	70	100.0	100.0	

Table 5 indicates the occupation that the respondents have. 84.3% said that they were employed, 8.6% said that they were self-employed, 5.7% said that they were students and 1.4% were unemployed.

Table 5: Occupation

Occupation	Frequency	Percent	Valid Percent	Cumulative Percent
Employed	59	84.3	84.3	84.3
Self-Employed	6	8.6	8.6	92.9
Student	4	5.7	5.7	98.6
Unemployed	1	1.4	1.4	100.0
Total	70	100.0	100.0	

were under the age of 30 and 44.3% indicated that they were between the ages of 31 -40. Whereas 24.3% indicated that they were between the ages of 41-50 and 10% were between the ages of 51-60. Only 4.3% of the respondents were older than 60Table 6 indicates the respondent break down by age group. 17.1% of the respondents indicated that they.

Table 6: Age Group

Age range	Frequency	Percent	Valid Percent	Cumulative Percent
18-30	12	17.1	17.1	17.1
31-40	31	44.3	44.3	61.4
41-50	17	24.3	24.3	85.7
51-60	7	10.0	10.0	95.7
Older than 60	3	4.3	4.3	100.0
Total	70	100.0	100.0	

Table 7 indicates the respondent break down by level of education. 57.1% of the respondents indicated that their highest level of education was a postgraduate qualification and 25.7% indicated a bachelor's degree as their highest qualification. Only 5.7% of the respondents indicated that their highest level of education was high school.

Table 7: Level of Education

	Frequency		Percent	Valid Percent	Cumulative Percent
Bachelor's degree	18		25.7	25.7	25.7
Diploma	8		11.4	11.4	37.1
High School	4		5.7	5.7	42.9

Postgraduate	40		57.1	57.1	100.0
Total	70		100.0	100.0	

Table 8: Cross-tabulation of Smart phone ownership and Use of mHealth Application

		Have you used a mobile health application?	**Total**
		Yes	
Do you own a smartphone?	Yes	70	70
Total		70	70

All the respondents who indicated to have owned a smartphone also indicated that they have used a mobile health application before as shown in Table 8.

Table 9: Cross-tabulation of Use of mHealth Application and Employment

		Have you used a mobile health application?	**Total**
		Yes	
Occupation	Employed	59	59
	Self-Employed	6	6
	Student	4	4
	Unemployed	1	1
Total		**70**	**70**

Table 9 represents the statistics on mHealth application usage and employment. Out of the 70 respondents who reported to have used a mHealth application, only one indicated to have been unemployed.

Table 10: Cross-tabulation of Gender and Use of mHealth Application

		Have you used a mobile health application?	**Total**
		Yes	
What is your gender?	Unspecified	1	1
	Female	41	41
	Male	28	28
Total		70	70

Table 10 represents the statistics on mHealth application usage and gender. Females represented 59% of the respondents who indicated to have used a mHealth application, whereas 40% of the respondents who indicated to have used a mHealth application were male.

Table 11: Level of Education and Use of Mhealth Application

		Have you used a mobile health application?	Total
		Yes	
Level of education	**Bachelor's degree**	18	18
	Diploma	8	8
	High School	4	4
	Postgraduate	40	40
Total		70	70

Table 11 represents the statistics on mHealth application usage and level of education. 40 out of the 70 respondents who indicated to have used a mHealth application indicated that their level of education was a postgraduate qualification.

4.3 Validity and Reliability

Reliability is the degree to which the measure of a construct maintains consistency. It refers to the notation that we should get the same results if we measure a construct multiple times (Bhattacherjee, 2012). Validity refers to the degree which a measure sufficiently represents the construct that it is supposed to measure (Bhattacherjee, 2012). The reliability and validity of the scales that were used to determine the factors that affect the use and acceptance of mHealth were determined using the Cronbach's Alpha test. This had to be determined before the model could be tested. The internal consistency (reliability) of the measurement scales were assessed through the Cronbach's alpha (α) coefficient. Cronbach's alpha measures if all items in a in a test evaluate the same construct or concept (Tavakol & Dennick, 2011). Data is deemed reliable and acceptable if the evaluated Cronbach's alpha is 0.70 or higher. The reliability statistics value was produced using SPSS for all the 22 items and had a value of 0.933. This indicates a reliable level of internal consistency for the scale. Table 12 represents these statistics.

Table 12: Internal Consistency Values

Cronbach's Alpha	N of Items
0.933	22

Table 13 shows the item-by-item statistics indicating what the Cronbach Alpha would be if an item is deleted. The Cronbach Alpha increases to 0.936 when mHealth provides ubiquitous service (TEC1) item is deleted. It also has the lowest Item-Total correlation indicating that it is not a good measure for the construct and that it may be dropped.

Table 13: Item-Total Correlation statistics

Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
TAC1	120.56	293.410	0.609	0.930
TAC2	120.70	291.401	0.646	0.930
TAC3	120.61	294.936	0.542	0.932
TEC1	121.23	310.875	0.243	0.936
TEC2	120.93	297.372	0.601	0.930
TEC3	121.31	287.030	0.676	0.929
TTF1	121.81	285.052	0.708	0.928
TTF2	121.60	286.272	0.752	0.928
TTF3	121.53	288.050	0.762	0.928
PEE1	120.99	296.304	0.619	0.930
PEE2	121.03	299.680	0.519	0.932
PEE3	121.30	287.981	0.747	0.928
EPE1	120.91	301.790	0.460	0.933
EPE2	120.99	300.420	0.465	0.933
EPE3	120.89	298.856	0.558	0.931
EPE4	120.93	295.343	0.660	0.929
FAC1	120.74	295.121	0.733	0.929
FAC2	120.93	293.111	0.687	0.929
FAC2	121.33	289.151	0.656	0.929
UAU1	120.70	300.416	0.668	0.930
UAU2	120.63	304.469	0.499	0.932
UAU3	120.56	306.163	0.493	0.932

Factor analysis is a data reduction method used to statistically group large number of items into a smaller set of variables based on their correlation patterns (Bhattacherjee, 2012). Factor analysis was used for variable reduction and to investigate the structure of the data. Before factor analysis was performed on

the data, the Kaiser-Meyer-Oklin (KMO) test was done to test that the sample size was sufficient for factor analysis. The KMO test measures whether the sampling was adequate (Shrestha, 2021a) for each construct in the model.

The calculated KMO value was 0.836 as shown in Table 14, therefore the data could be used for factor analysis as KMO values between 0.8 and 1.0 indicate that sampling is adequate (Shrestha, 2021b).
Bartlett's test was also run on the data to test the assumption that variances are homogenous across groups. A level of correlation between the variables must exist to run correlation analysis test. Bartlett's test aims to identify the correlation. By using SPSS, the value for Bartlett's was determined and for this study it was significant i.e., $p < 0.001$, therefore, showing that the correlation matrix has significant correlations amongst some of the variables indicating that using factor analysis was appropriate (Shrestha, 2021b).

Table 14: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.836
Bartlett's Test of Sphericity	**Approx. Chi-Square**	1219.110
	df	231
	Sig.	.000

Principal Component Analysis (PCA) was conducted with the seven factors that impact the adoption of mHealth adopted from the TTF and UTATUT models. The goal of principal component analysis is to extract important statistical information from the data (Nguyen, 2017). It was found that seven factors accounted for 82.6% of the total variance in the model as shown in Table 15. Coefficients of less than 0.40 were suppressed from the results for visual clarity. The Varimax method of rotation was used as it is found to minimize the number of variables which have high loadings on a factor to only have variables which load strongly on the factors.

Table 15: Principal Axis Factor Analysis

Total Variance Explained						
Component	**Initial Eigenvalues**			**Rotation Sums of Squared Loadings**		
	Total	**% Of Variance**	**Cumulative %**	**Total**	**% Of Variance**	**Cumulative %**
1	9.535	43.341	43.341	3.816	17.347	17.347
2	2.463	11.197	54.538	3.305	15.025	32.372
3	1.956	8.892	63.431	2.998	13.629	46.001
4	1.350	6.135	69.566	2.759	12.541	58.543
5	1.190	5.410	74.976	2.243	10.195	68.738
6	.960	4.362	79.338	1.572	7.145	75.882

7	.716	3.254	82.592	1.476	6.710	82.592
8	.605	2.751	85.343			
9	.509	2.315	87.658			
10	.447	2.033	89.692			
11	.392	1.781	91.472			
12	.345	1.567	93.040			
13	.254	1.155	94.195			
14	.235	1.069	95.264			
15	.212	.962	96.225			
16	.185	.842	97.068			
17	.153	.693	97.761			
18	.147	.666	98.427			
19	.140	.634	99.061			
20	.094	.426	99.487			
21	.068	.307	99.794			
22	.045	.206	100.000			
Extraction Method: Principal Component Analysis.						

The Rotated Component Matrix in Table 16 shows the loadings for the seven components. The third measure of Facilitating Conditions was observed to load into a different component (Effort Expectancy) from the other two measures of Facilitating Conditions. This measure was included as a measure of Effort Expectancy. Also, the second measure of Technology Characteristics was observed to also load into another component (Task Technology Fit) from the other two measures. Most of the items had a high loading value and thus indicated a high level of correlation with the constructs they were trying to measure.

Table 16: Rotated Factor Matrix

Rotated Component Matrix[a]							
	Component						
	1	2	3	4	5	6	7
TTF1	.800						
TTF2	.748						
EPE4	.698				.505		
TTF3	.682		.439				
TEC2	.572						.439
FAC3	.543				.519		
TAC1		.914					
TAC2		.905					
TAC3		.886					
PEE2			.907				
PEE1			.739				
PEE3			.702				
EPE2			.541		.454		
UAU2				.840			
UAU3				.839			
UAU1				.787			
EPE1			.442		.767		
EPE3					.736		
FAC2						.701	
FAC1						.677	
TEC3	.419	.434				.463	.410
TEC1							.893
Extraction Method: Principal Component Analysis. *Rotation Method: Varimax with Kaiser Normalization.*							
a. Rotation converged in 9 iterations.							

4.4 Normality Tests

Composite scores were calculated for each of the factors by averaging scores of the items measuring the variable. The composite scores were tested for normality to determine if they were a representative of a normally distributed population.

The Kolmogorov-Smirnov and Shapiro-Wilk is used to determine how well a random sample is evenly distributed (Şahintürk & Özcan, 2017). The two tests were used to compare the distributions of the data against reference normal distributions.

These tests yielded non-significance scores ($p<0.05$), which indicated that there was a significant deviation from the normal distribution. The conclusion on the distributions of the factors was to not assume normal distribution of the variables. This meant that non-parametric tests were used since the assumptions of normality were not met.

Table 17: Skewness and Kurtosis

Factor	Skewness	Kurtosis
UAU	-1.056	1.029
TTF	-0.864	1.378
TAC	-1.918	3.69
PEE	-0.753	0.177
EPE	-0.588	-0.525
FAC	-1.518	3.356
TEC	-0.676	0.224

Table 18: Tests of Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
UAU	.197	70	.000	.856	70	.000
TTF	.125	70	.009	.941	70	.003
TAC	.269	70	.000	.701	70	.000
PEE	.116	70	.021	.918	70	.000
EPE	.147	70	.001	.927	70	.001
FAC	.209	70	.000	.844	70	.000
TEC	.202	70	.000	.926	70	.001

a. Lilliefors Significance Correction

4.5 Correlation Analysis

Composite values of the independent and dependent constructs were computed in SPSS and correlation analysis was conducted to determine the strengths of the relationships between them. The Spearman correlation was used since the normality test showed that the distribution of factors does not follow a normal distribution (Mukaka, 2012).

Hypothesis 1

H1: Task characteristics of mHealth positively affect the Task Technology Fit.

Table 19: Correlation of Task Characteristics and Task Technology Fit

Correlations			**TAC**	**TTF**
Spearman's rho	TAC	Correlation Coefficient	1.000	.354**
		Sig. (2-tailed)	.	.003
		N	70	70
	TTF	Correlation Coefficient	.354**	1.000
		Sig. (2-tailed)	.003	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Task Characteristic and Task Technology Fit was found to be statistically significant (0.354, $p < 0.001$) at a weak level. This finding provides support for H1, that the higher the Task Characteristic, the higher the Task Technology Fit

Hypothesis 2

H2: Technology fit of mHealth positively affects the Task Technology Fit.

Table 20: Correlation of Technology Fit and Task Technology Fit

Correlations			**TTF**	**TEC**
Spearman's rho	TTF	Correlation Coefficient	1.000	.488**
		Sig. (2-tailed)	.	.000
		N	70	70
	TEC	Correlation Coefficient	.488**	1.000
		Sig. (2-tailed)	.000	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Technology Fit and Task Technology Fit was found to be statistically significant (0.488, $p < 0.01$) at a moderate level. This finding provides support for H2, that the higher the Technology Fit, the higher the Task Technology Fit.

Hypothesis 3

H3: Task Technology Fit has a positive influence on the use of mHealth.

Table 21: Correlation of Task Technology Fit and User Adoption of mHealth.

Correlations			**TTF**	**UAU**
Spearman's rho	TTF	Correlation Coefficient	1.000	.491**
		Sig. (2-tailed)	.	.000
		N	70	70
	UAU	Correlation Coefficient	.491**	1.000
		Sig. (2-tailed)	.000	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Task Technology Fit and the behavioral intention to adopt mHealth to be statistically significant (0.491, $p < 0.01$) at a moderate level. This finding provides support for H3, that the Task Technology Fit has a positive influence on the use of mHealth.

Hypothesis 4

H4: Performance Expectancy positively affects user adoption of mHealth.

Table 22: Correlation between Performance Expectancy and User Adoption of mHealth

Correlations			**PEE**	**UAU**
Spearman's rho	PEE	Correlation Coefficient	1.000	.397**
		Sig. (2-tailed)	.	.001
		N	70	70
	UAU	Correlation Coefficient	.397**	1.000
		Sig. (2-tailed)	.001	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Performance Expectancy and user adoption of mHealth technology was found to be statistically significant (0.397, $p < 0.01$) at a weak level. This finding provides support for H4, that Performance Expectancy has a positive influence on the use of mHealth.

Hypothesis 5

H5a: Effort Expectancy positively affects user adoption of mHealth.

Table 23: Correlation between Effort Expectancy and User Adoption of mHealth

Correlation			**EPE**	**UAU**
Spearman's rho	EPE	Correlation Coefficient	1.000	.518**
		Sig. (2-tailed)	.	.000
		N	70	70
	UAU	Correlation Coefficient	.518**	1.000
		Sig. (2-tailed)	.000	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Effort Expectancy and User Adoption Habit was found to be statistically significant (0.518, $p < 0.01$) at a moderate level. This finding provides support for H5a, that Effort Expectancy positively affects the user adoption of mHealth technology.

H5b: Effort Expectancy positively affects Performance Expectancy.

Table 24: Correlation between Effort Expectancy and User Performance Expectancy

Correlations			**PEE**	**EPE**
Spearman's rho	PEE	Correlation Coefficient	1.000	.489**
		Sig. (2-tailed)	.	.000
		N	70	70
	EPE	Correlation Coefficient	.489**	1.000
		Sig. (2-tailed)	.000	.
		N	**70**	**70**
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Performance Expectancy and Effort Expectancy was found to be statistically significant (0.489, $p < 0.01$) at a moderate level. This finding provides support for 5b, that Effort expectancy positively affects Performance Expectancy.

Hypothesis 6

H6: Facilitating Conditions significantly affect user adoption of mHealth technology.

Table 25: Correlation of Facilitating Conditions and User Adoption of mHeath.

Correlations			**FAC**	**UAU**
Spearman's rho	FAC	Correlation Coefficient	1.000	.645**
		Sig. (2-tailed)	.	.000
		N	70	70
	UAU	Correlation Coefficient	.645**	1.000
		Sig. (2-tailed)	.000	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Facilitating Conditions and user adoption of mHealth technology was found to be statistically significant (0.645, $p < 0.01$) at a strong level. This finding provides support for H6, that facilitating conditions positively affect user adoption of mHealth technology.

Hypothesis 7

H7: Task Technology Fit of mHealth has a positive relationship with Performance Expectancy.

Table 26: Correlation between Task Technology Fit and Performance Expectancy

Correlations			**TTF**	**PEE**
Spearman's rho	TTF	Correlation Coefficient	1.000	.694**
		Sig. (2-tailed)	.	.000
		N	70	70
	PEE	Correlation Coefficient	.694**	1.000
		Sig. (2-tailed)	.000	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Task was found to be statistically significant (0.694, $p < 0.01$) at a strong level. This finding provides support for H7, that Task Technology Fit of mHealth has a positive relationship with performance Expectancy.

Hypothesis 8

H8: Technology Characteristics of mHealth have a positive relationship with Effort Expectancy.

Table 27: Correlation between Technology Characteristics and Effort Expectancy

Correlations			**TEC**	**EPE**
Spearman's rho	TEC	Correlation Coefficient	1.000	.318**
		Sig. (2-tailed)	.	.007
		N	70	70
	EPE	Correlation Coefficient	.318**	1.000
		Sig. (2-tailed)	.007	.
		N	70	70
**. Correlation is significant at the 0.01 level (2-tailed).				

The relationship between Technology Characteristics and Effort Expectancy was found to be statistically significant (0.318, $p < 0.01$) at a weak level. This finding provides support for H8 that Technology Characteristics of mHealth have a significant relationship with Effort Expectancy.

Table 28 has a summary of the results related to testing the nine hypotheses for the relationships in the model.

Table 28: Summary of Hypothesis Testing Results

Construct	**Hypothesis Number and Description**	**Result**
Task Characteristics	H1: Task characteristics positively affect the Task Technology Fit	Supported
Technology Characteristics	H2: Technology fit of mHealth positively affects the Task Technology Fit	Supported
Task Technology Fit	H3: Task technology fit has a positive influence on the use of mHealth	Supported
Performance Expectancy	H4: Performance expectancy positively affects user adoption of mHealth	Supported
Effort Expectancy	H5a: Effort Expectancy positively affects user adoption of mHealth	Supported
	H5b: Effort Expectancy positively affects Performance Expectancy	Supported

Facilitating Conditions	H6: Facilitating conditions positively affects user adoption of mHealth technology	Supported
TTF and UTAUT	H7: Task technology fit of mHealth has a positive relationship with Performance Expectancy	Supported
	H8: Technology characteristics of mHealth have a positive relationship with Effort Expectancy	Supported

4.6 Multiple Regression

The proposed framework proposed the possible constructs that can have a significant impact on the user adoption of mHealth through the different hypotheses. The independent variables from the TTF theory are Task Characteristics and Technology characteristics and from the UTAUT theory, the independent variables are Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. The independent variable from the combined model is the Task Technology Fit. The dependent variable is the User Adoption of mHealth.

Since there is only one dependent variable and multiple independent variables related to it then multiple regression was used to assess how the independent variables predict the dependent variable (Ali & Younas, 2021).

Standard linear regression was carried out to determine the effect of each independent variable on the dependent variable.

Table 29: Multiple Regression Analysis Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.643[a]	.413	.357	.69228
a. Predictors: (Constant), TEC, EPE, TAC, PEE, FAC, TTF				

Table 30: ANOVA Results for Multiple Regression

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	21.268	6	3.545	7.396	.000[b]
	Residual	30.193	63	.479		
	Total	51.460	69			
a. Dependent Variable: UAU						
b. Predictors: (Constant), TEC, EPE, TAC, PEE, FAC, TTF						

Table 31: Multiple Regression Coefficients Results

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.777	.590		4.706	.000
	TTF	.106	.111	.144	.952	.345
	TAC	.006	.081	.009	.069	.945

	PEE	-.057	.101	-.073	-.560	.577
	EPE	.126	.113	.153	1.116	.269
	FAC	.336	.113	.420	2.970	.004
	TEC	.067	.109	.080	.612	.543
a. Dependent Variable: UAU						

The results of the ANOVA that were completed as part of the regression show that for the model, the F-value=7.396. This highlights that it is unlikely that this would have happened by chance ($p < 0.001$).

The F-value in regression is the result of a test where the null hypothesis is that all the regression coefficients are equal to zero. That is the model has no predictive capability.

Since $p < 0.05$, we reject the null hypothesis that all the predictors' coefficients are zero.

Standard linear regression was conducted on the adapted model comprising of TTF, TAC, PEE, EPE, FAC and TEC. The R^2 value indicates that the model accounted for a 41.3% variance of the user intention to adopt mHealth technology, indicating a very strong and statistically significant model. This is shown in the summary of the output, Table 31. Looking at the t-test of each predictor (independent variable), (t=2.970, p=0.004). Only FAC (Facilitating Conditions) was found to have a significant effect on the user intention to adopt mHealth technology at a significance level of 0.004, which is less than $p = 0.05$. TTF, TAC, PEE, EPE and TEC were found to have insignificant impact on the user intention to adopt mHealth, with levels of significance of 0.345, 0.945, 0.577 ,0.269 and 0.543 respectively.

Since the multiple regression analysis did not support the anticipated results, bivariate regression analysis was performed on the data for the individual factors and the combined models.

4.7 Regression Analysis

Multiple linear regression analysis was conducted to explore whether any of the predictor variables explain the dependent variable.

The study used the Bivariate Linear Regression Models to determine the factors that have a positive impact on user adoption according to the TTF theory, UTAUT theory and combined models respectively. It was conducted because it compares one independent variable and dependent variable one at a time (Ali & Younas, 2021).

4.7.1 The Regression analysis for the TTF Model

4.7.1.1 The effect of Task Characteristics on the user adoption of mHealth Technology

The study findings revealed that the Task Characteristics explained 11.6 % variation in user adoption of mHealth. The R^2 value indicates that the model accounted for a 11.6% variance of the User Intention to adopt mHealth technology as shown in the model summary in Table 32. This implies that 11.6% of the changes in adoption of mHealth technology could be explained by the task characteristics.

The results indicate that the model was statistically significant in linking task characteristics and user adoption of mHealth technology, f-value=8.963, $p < .05$. The model was important in explaining the relationship.

Table 32: Impact of Task Characteristics on the user adoption of mHealth Technology (Model Summary)

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.341[a]	.116	.103	.81770	.116	8.963	1	68	.004
a. Predictors: (Constant), TAC									

Table 33: Impact of Task Characteristics on the user adoption of mHealth Technology (ANOVA Results)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.993	1	5.993	8.963	.004[b]
	Residual	45.468	68	.669		
	Total	51.460	69			
a. Dependent Variable: UAU						
b. Predictors: (Constant), TAC						

A regression coefficient measures how sensitive the dependent variable is to changes in the independent variable. The magnitude and direction of the measure provides details pertaining to the extent to which changes in a variable affect the response variable. The results of the regression coefficient for Task Characteristics and user adoption of mHealth technology are shown in Table 33.

Table 34: Impact of Task Characteristics on the user adoption of mHealth Technology (Coefficients Results)

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.771	.469		10.184	.000
	TAC	.223	.075	.341	2.994	.004
a. Dependent Variable: UAU						

These study findings in Table 34 indicate that task characteristics positively and significantly predicts user adoption of mHealth technology, β = .223, t-statistic =2.994, p < .05. This indicates that a unit increase in task characteristic would lead to an increase in adoption of mHealth technology by 0.223 units. The study therefore concluded that task characteristics positively and significantly predicted user adoption of mHealth technology.

4.7.1.2 The effect of Technology Characteristics on the user adoption of mHealth Technology

The model was statistically significant with F-value= 10.714 and p=0.002. The R^2 =13.6% indicating that technology characteristics explains 13.6% of the variation in the user adoption of mHealth technology as shown in Table 35.

Table 35: Impact Technology Characteristics on the user adoption of mHealth Technology (Model Summary)

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.369[a]	.136	.123	.80855	.136	10.714	1	68	.002
a. Predictors: (Constant), TEC									

Table 36: Impact of Technology Characteristics on the user adoption of mHealth Technology (ANOVA)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7.005	1	7.005	10.714	.002[b]
	Residual	44.456	68	.654		
	Total	51.460	69			
a. Dependent Variable: UAU						
b. Predictors: (Constant), TEC						

Table 37: Impact of Technology Characteristics on the user adoption of mHealth Technology (Coefficients)

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.422	.534		8.275	.000
	TEC	.306	.094	.369	3.273	.002
a. Dependent Variable: UAU						

These study findings in Table 37 indicate that technology characteristics positively and significantly predict user adoption of mHealth technology, β = .306, t-statistic =3.273, p=0.002 which is less than the significance level: p<0.05.

The study therefore concluded that technology characteristics positively and significantly predicted the user adoption of mHealth technology.

4.7.2 The Regression analysis for the UTAUT Model

4.7.2.1 The effect of Performance Expectancy on the adoption of mHealth Technology

The model was statistically significant with F-value= 9.464 and p=0.003. The R^2=12.2% indicating that Performance Expectancy explains 12.2% of the variation in the user adoption of mHealth technology. This is shown in Table 38 below.

Table 38: Impact of Performance Expectancy on the adoption of mHealth Technology (Model Summary)

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.350[a]	.122	.109	.81506	.122	9.464	1	68	.003
a. Predictors: (Constant), PEE									

Table 39: Impact of Performance Expectancy on the adoption of mHealth Technology (ANOVA)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6.287	1	6.287	9.464	.003[b]
	Residual	45.173	68	.664		
	Total	51.460	69			
a. Dependent Variable: UAU						

b. Predictors: (Constant), PEE

Table 40: Impact of Performance Expectancy on the adoption of mHealth Technology (Coefficients)

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.609	.508		9.070	.000
	PEE	.271	.088	.350	3.076	.003
a. Dependent Variable: UAU						

These study findings in Table 40 above indicate that Performance Expectancy positively and significantly predicts the user adoption of mHealth technology, β = .271, t-statistic =3.076, p=0.003 which is less than the significance level: p<0.05.

The study therefore concluded that Performance Expectancy positively and significantly predicted the user adoption of mHealth technology.

4.7.2.2 The effect of Effort Expectancy on the adoption of mHealth Technology

The model was statistically significant with F-value= 23.665 and p<0.05. The R^2 =25.8% meaning that Effort Expectancy explains 25.8% of the variation in the user adoption of mHealth technology. This is shown in Table 41 below.

Table 41: The effect of Effort Expectancy on the adoption of mHealth Technology (Model Summary)

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.508[a]	.258	.247	.74926	.258	23.665	1	68	.000
a. Predictors: (Constant), EPE									

Table 42: The effect of Effort Expectancy on the adoption of mHealth Technology (ANOVA)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.286	1	13.286	23.665	.000[b]
	Residual	38.175	68	.561		
	Total	51.460	69			
a. Dependent Variable: UAU						

b. Predictors: (Constant), EPE

Table 43: The effect of Effort Expectancy on the adoption of mHealth Technology (Coefficients

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.735	.503		7.424	.000
	EPE	.420	.086	.508	4.865	.000
a. Dependent Variable: UAU						

The model was statistically significant with F-value= 23.665 and p<0.05. The R^2 =25.8% meaning that Effort Expectancy explains 25.8% of the variation in the user adoption of mHealth technology. These study findings in table 43 indicate that Effort Expectancy positively and significantly predicts user adoption of mHealth technology, β = .420, t-statistic =4.865, p=0.000 which is less than the significance level: p<0.05. The study therefore concluded that Effort Expectancy positively and significantly predicted the user adoption of mHealth technology.

4.7.2.3 The effect of Facilitating Conditions on the adoption of mHealth Technology

The model was statistically significant with F-value= 40.487 and p<0.05. The R^2= 37.3% indicating that facilitating conditions explains 37.3% of the variation in the user adoption of mHealth technology. This is shown in Table 44 below.

Table 44: The effect of Facilitating Conditions on the adoption of mHealth Technology (Model Summary)

Model Summary									
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.611[a]	.373	.364	.68873	.373	40.487	1	68	.000
a. Predictors: (Constant), FAC									

Table 45: The effect of Facilitating Conditions on the adoption of mHealth Technology (ANOVA)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	19.205	1	19.205	40.487	.000[b]
	Residual	32.255	68	.474		
	Total	51.460	69			
a. Dependent Variable: UAU						
b. Predictors: (Constant), FAC						

Table 46: The effect of Facilitating Conditions on the adoption of mHealth Technology (Coefficients)

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3.243	.463		7.002	.000
	FAC	.489	.077	.611	6.363	.000
a. Dependent Variable: UAU						

These study findings in Table 46 indicate that facilitating conditions positively and significantly predict user adoption of mHealth technology, β = .489, t-statistic =6.383, p=0.000 which is less than the significance level: p<0.05.

The study therefore concluded that facilitating conditions positively and significantly predicted the user adoption of mHealth technology.

4.7.3 The Regression analysis for the Combined Model

4.7.3.1 The effect of Task Technology Fit on the adoption of mHealth Technology.

Table 47: The effect of Task Technology Fit on the adoption of mHealth Technology (Model Summary)

Model Summary									
					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.502[a]	.252	.241	.75229	.252	22.928	1	68	.000
a. Predictors: (Constant), TTF									

Table 48: The effect of Task Technology Fit on the adoption of mHealth Technology (ANOVA)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12.976	1	12.976	22.928	.000[b]
	Residual	38.484	68	.566		
	Total	51.460	69			

a. Dependent Variable: UAU

b. Predictors: (Constant), TTF

Table 49: The effect of Task Technology Fit on the adoption of mHealth Technology (Coefficients)

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	4.184	.419		9.988	.000
	TTF	.369	.077	.502	4.788	.000

a. Dependent Variable: UAU

The combined model was statistically significant with F-value= 22.928 and $p<0.05$. The R^2 = 25.2% meaning that Task Technology Fit explains 25.2% of the variation in the user adoption of mHealth technology. This is shown in table 47. The study findings indicates that task-technology fit positively and significantly predicts user adoption of mHealth technology, β = .369, t-statistic =4.788, $p< 0.05$. The study therefore concluded that Task Technology Fit positively and significantly predicted the user adoption of mHealth technology. This is shown in Table 49

4.7.4 Summary of Findings

The purpose of this section is to conclude the chapter with a summary of the hypothesis findings, as shown in below Table 50.

Table 50: Results of Hypothesis testing (Summary)

Hypotheses	**Path coefficients (β)**	**t-value**	**p-value**	**Support**
H1: Task Characteristics significantly affect the Task Technology Fit	0.223	2.994	P<0.5	Yes
H2: Technology fit of mHealth significantly affects the Task Technology Fit	0.306	3.273	P=0.002	Yes
H3: Task Technology Fit has a positive influence on the use of mHealth	0.369	4.788	P<0.05	Yes
H4: Performance Expectancy significantly affects user adoption of mHealth	0.271	3.076	P=0.003	Yes
H5a: Effort Expectancy significantly affects user adoption of mHealth	0.420	4.865	P=0000	Yes
H6: Facilitating Conditions significantly affect user adoption of mHealth technology	0.489	6.383	P=0000	Yes

CHAPTER 5: DISCUSSION

The purpose of this chapter is to discuss the findings of the study and how the research questions and objectives of the study were addressed. The chapter is divided into two sections, research findings as they relate to the TTF framework and research the findings as they relate to the UTAUT framework.

5.1 Effects of TTF factors on mHealth adoption

The first research question that the study aimed to answer was as follows: What are the factors that affect the use and acceptance of mHealth applications by individual adult users in the South African health sector? The research question was addressed by conducting statistical analysis on data collected during the study to evaluate the significance of hypotheses that emanated from TTF and UTAUT constructs. This led to also answering the second and third research questions, which were related to identifying the task and technology characteristics that affect the acceptance of mHealth respectively. Seven factors were identified as having the potential to impact the adoption of mHealth technology in South Africa, answering the fourth research question. These factors were Task Characteristics, Technology Characteristics, Task-Technology Fit, Performance Expectancy, Facilitating Conditions and Effort Expectancy. All the factors were identified as having a positive impact on the user adoption of mHealth technology when tested individually through statistical analysis.

5.1.1 Task Characteristics

The study investigated the impact of task characteristics on the adoption of mHealth technology. The study hypothesized that task technology characteristics have a positive impact on the adoption of mHealth technology. The study results were in support of the hypothesis, supporting that there is a positive correlation between the task characteristics of an mHealth technology innovation and its subsequent adoption. Therefore, the adoption of mHealth technology will increase as the value of its task characteristics increase. For instance, if there is a new mHealth technology and it is a good fit for a particular health related task such as reminding patients to take their meds, the technology is likely to be adopted if it fits to the task that it is meant to be automating. It can be linked to how complex the task requirements are. Task fit is contextual and relates to the task that the mHealth application is meant to support, so designers need to consider the user during requirements gathering. A higher task fit will push users towards heavy reliance on the mHealth application, hence potentially increasing its adoption. The study results are consistent with findings from other studies (Wang et al., 2020a; Zhou et al., 2010b; (Omotayo & Haliru, 2020).

5.1.2 Technology Characteristics

The study investigated the impact of technology characteristics on the adoption of mHealth technology. The study hypothesized that technology characteristics have a positive impact on the adoption of mHealth technology. The study results were in support of the hypothesis, supporting that there is a positive correlation between the adoption of an mHealth technology innovation and its technology characteristics. This is indicative of the fact that technological characteristics such as the technology's design and ease of use will have a positive impact on its adoption. So, if an innovation is designed with the users in mind, taking into consideration the capabilities of the users the technology is meant to support then it is likely to be adopted. So, if designers build an mHealth innovation that users find difficult to use, usage is likely to decrease and in turn decrease the potential adoption of the innovation. The study results are consistent with findings from other studies (Wang et al., 2020a; (Omotayo & Haliru, 2020).

5.1.3 Task-Technology Fit

The study investigated the impact of task-technology fit characteristics on the adoption of mHealth technology. The study hypothesized that task-technology fit characteristics have a positive impact on the adoption of mHealth technology. The study results were in support of the hypothesis, supporting that there is a positive correlation between the adoption of an mHealth technology innovation and its task-technology fit characteristics. For instance, if the timeliness and ease of use of an mHealth application to measure adherence to medication meets the user's health management task of keeping track of their adherence, the task-technology fit would increase. Whereas, in contrast if the task of managing the adherence is to complex and time consuming, the Task-Technology Fit will be negatively impacted. mHealth designers should build the functionalities of the innovation with the idea of making the task the innovation supports easier. The study results are also consistent with other adoption studies in the health sector (Nurhayati et al., 2019; Khan et al., 2018).

5.2 Effects of UTAUT factors on mHealth adoption

5.2.1 Performance Expectancy

The study investigated the impact of Performance Expectancy on the adoption of mHealth technology. The study hypothesized that Performance Expectancy has a positive impact on the adoption of mHealth technology. Study findings were in support of the hypothesis, supporting that there is a positive correlation between Performance Expectancy of an mHealth innovation and its adoption. The finding suggests that the level which users believe an mHealth technology innovation will add value to a particular task that the technology automates, the better the chances of the technology getting adopted. This finding is consistent with other studies related to mHealth adoption (Alam et al., 2020; Shiferaw et all, 2019). The findings suggest that mHealth designers should include potential users and understanding their needs when designing a new mHealth innovation, as this will potentially increase a technology's usefulness to the users. Developing an mHealth application which adds value for the user and alleviates some burden that was caused by a manual task might increase it adoption and subsequent use.

5.2.2 Effort Expectancy

The study investigated the impact of Effort Expectancy on the adoption of mHealth technology. The study hypothesized that Effort Expectancy has a positive impact on the adoption of mHealth technology. Study findings were in support of the hypothesis, supporting that there is a positive correlation between Effort Expectancy of an mHealth innovation and its adoption. Effort Expectancy was found to have a higher impact in predicting the behavioural intention to use an mHealth adoption. This was contradicting the study by Wang et al., which found it to have a smaller impact (Wang et al., 2020b). The easier or simpler it is to use an mHealth application, the more likely it is to be adopted. Technology designers who invest in understanding the type of users who will use the mHealth innovation they are designing the mHealth tool for are likely to increase the adoption of the mHealth innovation. This may also benefit countries like South Africa where some remote parts of the country have an influx of users with a low technology literacy level and could benefit from an mHealth innovation in manging their health.

5.2.2 Facilitating Conditions

The study investigated the impact of facilitating conditions on the adoption of mHealth technology. The study hypothesized that facilitating conditions has a positive impact on the adoption of mHealth technology. Study findings were in support of the hypothesis, supporting that there is a positive correlation between effort facilitating conditions of an mHealth innovation and its adoption. Facilitating conditions refer to how an individual user's perception that there is infrastructure and support of an mHealth innovation. This could be conditions such as ensuring that an mHealth tool is approved or supported by important health related bodies such as WHO/government and there is helpdesk support for the mHealth innovation. The results of the study found facilitating conditions to be a very important factor in mHealth adoption with it explaining 37.4% of the variation in the user adoption of mHealth technology. This may be an indicator that users feel at ease to use an application for their health needs when it is supported, and the application has buy-in from structures the users deem as important. The high correlation is also synonymous with other study findings (Nurhayati et al., 2019; Shiferaw et all, 2019). This finding should motivate government organizations to invest in infrastructure and policies to support mHealth initiatives in the health sector. South Africa has already started by including mHealth in its strategy, but this can be strengthened with a supportive environment and infrastructure.

CHAPTER 6: CONCLUSION

6.1 Summary of Findings

The study aimed to answer one primary question and two secondary questions. The first objective of the study was to identify the factors that impact the adoption of mHealth. This was done through reviewing existing literature to identify mHealth adoption factors through the lens of TTF and UTAUT. An online questionnaire was then disseminated to test the adoption factors. This was aimed at answering the primary question related to factors that affect the adoption of mHealth in the health sector in South Africa.

The first research objective was to identify the factors that affect the user acceptance and use of mHealth in the South African health sector. To achieve this, exploratory factor analysis was used to extract the seven constructs/factors as adopted from the model. The seven factors were extracted, and the results returned had a slight deviation from the items that were suggested by the literature review. The deviation was due to items that were overlapping or loading high on more than one construct.

The study also looked at multiple hypotheses which were proposed because of the literature review. Correlation analysis was conducted to determine the strengths of the relationships between the identified factors as hypothesized in chapter 2. The Spearman correlation was used since the normality test showed that the distribution of factors does not follow a normal distribution.

The third objective of the study was to determine the significant factors in the UTAUT and TTF models that affect the adoption of mHealth in the South African health sector. The study first looked at multiple regression with the UAU being the dependent variable and the following factors being independent variables TEC, EPE, TAC, PEE, FAC, TTF. The results showed a very strong and statistically significant model with The R^2 =41.3%. The R^2 value indicated that the model accounted for a 41.3% variance of the user intention to adopt mHealth technology. However, it was also observed that the results suggested that only FAC (Facilitating Conditions) was significant in positively predicting the user acceptance and adoption of the mHealth technology with (t=2.970, p=0.004).

Other researchers continued to adopt similar models as the R^2 was significant and the model was significant at the 5% significance level. They also included predictors that were not statistically significant in their final model of the adoption of mHealth technology.

The last objective was to conceptualize a model for the adoption of mHealth in the South African context. To develop a statistically significant model, multiple linear regression models were carried out to determine the effect of each independent variable on the dependent variable. This was done as per the adopted TTF model, UTAUT model and the combined model. The regression analyses results showed that each individual factor significantly predicted the user acceptance and adoption of mHealth technology. That is each factor had a positive impact on the adoption of mHealth. It is therefore recommended to have multiple models to better understand the adoption of mHealth technology in this context.

6.2 Implications for Academia

A gap in terms of literature that analyses the acceptance and use of mHealth technology in South Africa is visible from extensive literature search. The proposed study contributed to the body of knowledge by developing a model for the acceptance and use of mobile health applications in the South African context. Adding both a theoretical and contextual contribution. Literature also indicated a gap in a mHealth innovations moving beyond the pilot phase, indicating that the topic of mHealth adoption should be explored further. This study can act as a basis for other academics who wish to explore the topic further. Most studies found that the combined model of TTF and UTAUT were significant in testing for the adoption of mHealth studies, whereas this study found it to not be significant and found that multiple models should be used to test for the adoption of mHealth in this context. This study could also serve as a basis for academics who want to further understand conditions which the combined models is not significant in the adoption of mHealth technology. mHealth adoption beyond the pilot phase is still high, this study could be used as a baseline to better understand the results reported in the data analysis of the report. For instance, researchers could focus on understanding the reasons that facilitating conditions had a very impact on the adoption of mHealth or even understanding the reasons why Effort Expectancy had a high impact as well.

6.3 Implications for Practice

mHealth applications have the potential to improve the way health care workers perform their health-related tasks and can also improve the way patients manage their health-related activities to manage their health (Alam et al., 2021). A suggested solution to overcoming the issue of scalability is to build mHealth applications which consider the user and usability (Wallis et al., 2017). The model will assist decision makers with factors to consider when moving towards considering users and usability. mHealth technology designers should design technology that is sufficient to manage the health-related task it is intended to manage in an easy way. Furthermore, technology designers should also try to build

technology that follows the standards of important health related bodies such as the WHO or government organizations. Facilitating conditions was found to be highly significant so building technology that is supported has the potential to increase the adoption rate of an mHealth innovation being adopted. Task characteristics was found to have a positive effect on the adoption of mHealth, so technology designers/providers should build solutions that caters for a specific health management related tasks to meet requirements of a diverse pool of users. The capabilities of users also need to be taken into consideration to ensure that the functionalities of the mHealth tool are easy to use.

6.4 Limitations

The study had several limitations which we have highlighted in this section. There was a low number of articles related to mHealth scalability in South Africa so to increase the number of articles reviewed, articles related to scalability in developing countries were included. The study excluded 37 responses from participants who had indicated to not have used mHealth before due to incomplete data. This could create a bias in the study findings since only those who have used mHealth applications were included. The study conducted data analysis on 70 responses, which may be considered a small sample size and make it difficult to generalize as started by (Bhattacherjee, 2012). Generalizing the results of the study to the South African population may be difficult due to this. The study was meant to only include respondents from Gauteng, even though the study had no method of identifying the exact region in Gauteng and in turn making it difficult to understand the coverage. So as a result, the ability to generalize the results to a wider geographical context such as South Africa or Gauteng may have been compromised. This generalization limitation may impact external validity which can be impacted be impacted by demographic info exclusion (Andrade, 2018). Since the study was a fully quantitative study there was a limitation related that. The study had pre-set answers which could possibly cause the true feelings/thoughts of the respondents to not be fully reflected in their responses and in turn limiting the outcome of the research (Taherdoost, 2022). Most of the sources used in the study were older than 5 years, so new context may be missing from the research.

6.5 Future Work

The model can be further extended to study a specific mobile health application's adoption in relation to managing a specific disease, example studying the impact of SMS reminders for adherence to chronic medication. The theory can also be expanded to include other models. Only facilitating conditions were found to be significant for the combined model of UTAUT and TTF in this study's context contradicting most studies, more research into why the results were inconsistent with other studies in this context could

be undertaken. Task-technology was found to be significant, more specifically relating to the tasks and technology characteristics of the mHealth innovation. A study on mHealth adoption using just TTF in the South African context to better understand the relationship between tasks the innovation automates, and the technology characteristics could be pursued. Facilitating conditions was also found to be highly significant in the context of mHealth adoption in South Africa, further studies on how supporting structures such as the government can be involved in the adoption of an mHealth innovation can be conducted. The study being purely quantitative creates a limitation in terms of the depth of detail such as feelings, thoughts and behaviours so other researchers could explore the factors that affect mHealth adoption through the lens of a qualitative study.

6.6 Conclusion

This study has contributed to existing literature by identifying the factors that affect mHealth adoption. The adoption of the factors was done by reviewing literature pertaining to adoption from a TTF and UTAUT perspective. Quantitative data analysis techniques were then used to understand the relationship between the factors and their impact on the model. It was found that all the identified factors were important in trying to understand the adoption patterns of an mHealth innovation in South Africa. This study offered a unique perspective to literature gaps through the analysis of the individual models as the combined model was found to be statistically insignificant. mHealth can really bring about a positive change in how patients manage their health and how healthcare workers interact with patients. Studies like this one provide a lens into design decisions that need to be considered to bring us a step closer to institutionalizing mHealth in the South African health sector.

REFERENCES

011_who_afro_scaling_health_innovations_in_africa_a4_v1_20210108084959.pdf. (n.d.). Retrieved October 2, 2022, from https://innov.afro.who.int/uploads/media-corner/011_who_afro_scaling_health_innovations_in_africa_a4_v1_20210108084959.pdf

Abaza, H., & Marschollek, M. (2017). mHealth Application Areas and Technology Combinations. *Methods of Information in Medicine*, *56*(Suppl 1), e105–e122. https://doi.org/10.3414/ME17-05-0003

Addotey-Delove, M., Scott, R. E., & Mars, M. (2023). Healthcare Workers' Perspectives of mHealth Adoption Factors in the Developing World: Scoping Review. *International Journal of Environmental Research and Public Health*, *20*(2), 1244. https://doi.org/10.3390/ijerph20021244

Agbenyo, J. S. T. E. P. H. E. N. (2019). A Review of Factors that Increases or Reduces the Adoption of mHealth. *International Journal of Research and Scientific Innovation*. https://www.academia.edu/41556066/A_Review_of_Factors_that_Increases_or_Reduces_the_Adoption_of_mHealth

Alaiad, A., Alsharo, M., & Alnsour, Y. (2019). The Determinants of M-Health Adoption in Developing Countries: An Empirical Investigation. *Applied Clinical Informatics*, *10*(5), 820–840. https://doi.org/10.1055/s-0039-1697906

Alam, M., Hu, W., & Gani, M. (2019). An Empirical Analysis of the Influencing Factors of Adoption of Mobile Health Services in Bangladesh Based on Extended UTAUT Model. *WHICEB 2019 Proceedings*. https://aisel.aisnet.org/whiceb2019/53

Alam, M. M. D., Alam, M. Z., Rahman, S. A., & Taghizadeh, S. K. (2021). Factors influencing mHealth adoption and its impact on mental well-being during COVID-19 pandemic: A SEM-ANN approach. *Journal of Biomedical Informatics*, *116*, 103722. https://doi.org/10.1016/j.jbi.2021.103722

Alam, M. Z., Hoque, Md. R., Hu, W., & Barua, Z. (2020). Factors influencing the adoption of mHealth services in a developing country: A patient-centric study. *International Journal of Information Management*, *50*, 128–143. https://doi.org/10.1016/j.ijinfomgt.2019.04.016

Ali, P., & Younas, A. (2021). Understanding and interpreting regression analysis. *Evidence-Based Nursing*, *24*(4), 116–118. https://doi.org/10.1136/ebnurs-2021-103425

Andrade, C. (2018). Internal, External, and Ecological Validity in Research Design, Conduct, and Evaluation. *Indian Journal of Psychological Medicine*, *40*(5), 498–499. https://doi.org/10.4103/IJPSYM.IJPSYM_334_18

Anstey Watkins, J. O. T., Goudge, J., Gómez-Olivé, F. X., & Griffiths, F. (2018). Mobile phone use among patients and health workers to enhance primary healthcare: A qualitative study in rural South Africa. *Social Science & Medicine (1982)*, *198*, 139–147. https://doi.org/10.1016/j.socscimed.2018.01.011

Antwi, S. K., & Hamza, K. (2015). Qualitative and Quantitative Research Paradigms in Business Research: A Philosophical Reflection. *European Journal of Business and Management*, 11.

Arfi, W. B., Nasr, I. B., Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, *167*, 120688. https://doi.org/10.1016/j.techfore.2021.120688

Ayaz, A., & Yanartaş, M. (2020). An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). *Computers in Human Behavior Reports*, *2*, 1–7. https://doi.org/10.1016/j.chbr.2020.100032

Ayuning Budi, N. F., Adnan, H. R., Firmansyah, F., Hidayanto, A. N., Kurnia, S., & Purwandari, B. (2021). Why do people want to use location-based application for emergency situations? The extension of UTAUT perspectives. *Technology in Society*, *65*, 101480. https://doi.org/10.1016/j.techsoc.2020.101480

Balapour, A., Reychav, I., Sabherwal, R., & Azuri, J. (2019). Mobile technology identity and self-efficacy: Implications for the adoption of clinically supported mobile health apps. *International Journal of Information Management*, *49*, 58–68. https://doi.org/10.1016/j.ijinfomgt.2019.03.005

Barutçu, S. (2018). *A technology acceptance analysis for mhealth apps: The case of Turkey*. https://www.academia.edu/64841786/A_technology_acceptance_analysis_for_mhealth_apps_the_case_of_Turkey

Bervell, B., & Al-Samarraie, H. (2019). A comparative review of mobile health and electronic health utilization in sub-Saharan African countries. *Social Science & Medicine*, *232*, 1–16. https://doi.org/10.1016/j.socscimed.2019.04.024

Bhattacherjee, A. (2012). Social Science Research: Principles, Methods, and Practices. *Textbooks Collection*. https://scholarcommons.usf.edu/oa_textbooks/3

Bhochhibhoya, S., Dobbs, P. D., & Maness, S. B. (2021). Interventions using mHealth strategies to improve screening rates of cervical cancer: A scoping review. *Preventive Medicine*, *143*, 106387. https://doi.org/10.1016/j.ypmed.2020.106387

Botha, A., & Booi, V. (2016). mHealth implementation in South Africa. *2016 IST-Africa Week Conference*, 1–13. https://doi.org/10.1109/ISTAFRICA.2016.7530667

Brinkel, J., May, J., Krumkamp, R., Lamshöft, M., Kreuels, B., Owusu-Dabo, E., Mohammed, A., Marinovic, A., Dako-Gyeke, P., Krämer, A., & Fobil, J. (2017). Mobile phone-based interactive voice response as a tool for improving access to healthcare in remote areas in Ghana—An evaluation of user experiences. *Tropical Medicine & International Health*, *22*. https://doi.org/10.1111/tmi.12864

Chaiyachati, K. H., Loveday, M., Lorenz, S., Lesh, N., Larkan, L.-M., Cinti, S., Friedland, G. H., & Haberer, J. E. (2013). A pilot study of an mHealth application for healthcare workers: Poor uptake despite high reported acceptability at a rural South African community-based MDR-TB treatment program. *PloS One*, *8*(5), e64662. https://doi.org/10.1371/journal.pone.0064662

Choi, S. A., Lim, K., Baek, H., Yoo, S., Cho, A., Kim, H., Hwang, H., & Kim, K. J. (2021). Impact of mobile health application on data collection and self-management of epilepsy. *Epilepsy & Behavior*, *119*, 107982. https://doi.org/10.1016/j.yebeh.2021.107982

Cimperman, M., Makovec Brenčič, M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior—Applying an Extended UTAUT model. *International Journal of Medical Informatics*, *90*, 22–31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Comulada, W. S., Wynn, A., van Rooyen, H., Barnabas, R. V., Eashwari, R., & van Heerden, A. (2019). Using mHealth to Deliver a Home-Based Testing and Counseling Program to Improve Linkage to Care and ART Adherence in Rural South Africa. *Prevention Science*, *20*(1), 126–136. Scopus. https://doi.org/10.1007/s11121-018-0950-1

cscscholarship. (2018, June 19). Explanatory Research Definition |Explanatory Research Example | explanatory Research Question. *Chinese Government Scholarship 2019 | Apply Online*. https://www.chinesescholarshipcouncil.com/explanatory-research.html

DeLone, W. H., & McLean, E. R. (1992). Information Systems Success: The Quest for the Dependent Variable. *Information Systems Research*, *3*(1), 60–95. https://doi.org/10.1287/isre.3.1.60

Gan, Q. (2015). Is the adoption of electronic health record system "contagious"? *Health Policy and Technology*, *4*(2), 107–112. https://doi.org/10.1016/j.hlpt.2015.02.009

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213–236. https://doi.org/10.2307/249689

Gous, N., Fischer, A. E., Rhagnath, N., Phatsoane, M., Majam, M., & Lalla-Edward, S. T. (2020). Evaluation of a mobile application to support HIV self-testing in Johannesburg, South Africa. *Southern African Journal of HIV Medicine*, *21*(1), Article 1.

Govender, K., Beckett, S., Masebo, W., Braga, C., Zambezi, P., Manhique, M., George, G., & Durevall, D. (2019). Effects of a Short Message Service (SMS) Intervention on Reduction of HIV Risk

Behaviours and Improving HIV Testing Rates Among Populations located near Roadside Wellness Clinics: A Cluster Randomised Controlled Trial in South Africa, Zimbabwe and Mozambique. *AIDS and Behavior*, *23*(11), 3119–3128. https://doi.org/10.1007/s10461-019-02427-6

Guetterman, T. C. (2019). Basics of statistics for primary care research. *Family Medicine and Community Health*, *7*(2), e000067. https://doi.org/10.1136/fmch-2018-000067

Healthcare apps available Google Play 2021. (n.d.). Statista. Retrieved June 13, 2021, from https://www.statista.com/statistics/779919/health-apps-available-google-play-worldwide/

Hood, M., Wilson, R., Corsica, J., Bradley, L., Chirinos, D., & Vivo, A. (2016). What do we know about mobile applications for diabetes self-management? A review of reviews. *Journal of Behavioral Medicine*, *39*(6), 981–994. https://doi.org/10.1007/s10865-016-9765-3

Hossain, M. A., Quaresma, R., & Rahman, M. (2018). Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: An empirical study. *International Journal of Information Management*, *44*, 76–87. https://doi.org/10.1016/j.ijinfomgt.2018.09.016

Isaac, O., Abdullah, Z., Aldholay, A. H., & Abdulbaqi Ameen, A. (2019). Antecedents and outcomes of internet usage within organisations in Yemen: An extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. *Asia Pacific Management Review*, *24*(4), 335–354. https://doi.org/10.1016/j.apmrv.2018.12.003

Istepanian, R. S., Kulhandjian, M., & Chaltikyan, G. (2020). Mobile Health (mHealth) in the Developing World: Two Decades of Progress or Retrogression. *Journal of the International Society for Telemedicine and eHealth*, *8*, e24 (1-5). https://doi.org/10.29086/JISfTeH.8.e24

Jewer, J. (2018). Patients' intention to use online postings of ED wait times: A modified UTAUT model. *International Journal of Medical Informatics*, *112*, 34–39. https://doi.org/10.1016/j.ijmedinf.2018.01.008

Jonker, J., & Pennink, B. (2010). *The Essence of Research Methodology: A Concise Guide for Master and PhD Students in Management Science*. Springer Berlin Heidelberg.

Junglas, I., Abraham, C., & Ives, B. (2009). Mobile technology at the frontlines of patient care: Understanding fit and human drives in utilization decisions and performance. *Decision Support Systems*, *46*(3), 634–647. https://doi.org/10.1016/j.dss.2008.11.012

Kabir, S. M. (2016). *METHODS OF DATA COLLECTION* (pp. 201–275).

Kaium, M. A., Bao, Y., Alam, M. Z., Hasan, N., & Hoque, M. R. (2019). Understanding the insight of factors affecting mHealth adoption. *International Journal of Research in Business and Social Science (2147- 4478)*, *8*(6), 181.

Kauta, N. J., Groenewald, J., Arnolds, D., Blankson, B., Omar, A., Naidu, P., Naidoo, M., & Chu, K. M. (2020). WhatsApp Mobile Health Platform to Support Fracture Management by Non-Specialists in South Africa. *Journal of the American College of Surgeons*, *230*(1), 37–42. https://doi.org/10.1016/j.jamcollsurg.2019.09.008

Kruse, C., Betancourt, J., Ortiz, S., Luna, S. M. V., Bamrah, I. K., & Segovia, N. (2019). Barriers to the Use of Mobile Health in Improving Health Outcomes in Developing Countries: Systematic Review. *Journal of Medical Internet Research*, *21*(10), e13263. https://doi.org/10.2196/13263

Kumar, D. S., Purani, K., & Viswanathan, S. A. (2018). Influences of 'appscape' on mobile app adoption and m-loyalty. *Journal of Retailing and Consumer Services*, *45*, 132–141. https://doi.org/10.1016/j.jretconser.2018.08.012

Kumar, R. (2014). *Research methodology: A step-by-step guide for beginners* (3rd ed). SAGE.

Latif, S., Rana, R., Qadir, J., Ali, A., Imran, M. A., & Younis, M. S. (2017). Mobile Health in the Developing World: Review of Literature and Lessons From a Case Study. *IEEE Access*, *5*, 11540–11556. https://doi.org/10.1109/ACCESS.2017.2710800

Laugesen, J., & Hassanein, K. (2017). Adoption of personal health records by chronic disease patients: A research model and an empirical study. *Computers in Human Behavior*, *66*, 256–272. https://doi.org/10.1016/j.chb.2016.09.054

Leon, N., Surender, R., Bobrow, K., Muller, J., & Farmer, A. (2015). Improving treatment adherence for blood pressure lowering via mobile phone SMS-messages in South Africa: A qualitative evaluation of the SMS-text Adherence SuppoRt (StAR) trial. *BMC Family Practice*, *16*(1), 80. https://doi.org/10.1186/s12875-015-0289-7

Lu, D. J., Girgis, M., David, J. M., Chung, E. M., Atkins, K. M., & Kamrava, M. (2021). Evaluation of Mobile Health Applications to Track Patient-Reported Outcomes for Oncology Patients: A Systematic Review. *Advances in Radiation Oncology*, *6*(1), 100576. https://doi.org/10.1016/j.adro.2020.09.016

Macedo, I. M. (2017). Predicting the acceptance and use of information and communication technology by older adults: An empirical examination of the revised UTAUT2. *Computers in Human Behavior*, *75*, 935–948. https://doi.org/10.1016/j.chb.2017.06.013

Maillet, É., Mathieu, L., & Sicotte, C. (2015). Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT. *International Journal of Medical Informatics*, *84*(1), 36–47. https://doi.org/10.1016/j.ijmedinf.2014.09.004

McCreesh-Toselli, S., Torline, J., Gouse, H., Robbins, R. N., Mellins, C. A., Remien, R. H., Rowe, J., Peton, N., Rabie, S., & Joska, J. A. (2021). Staff perceptions of preimplementation barriers and facilitators to a mobile health antiretroviral therapy adherence counseling intervention in south africa: Qualitative study. *JMIR mHealth and uHealth*, *9*(4). Scopus. https://doi.org/10.2196/23280

Mehl, G. L., Tamrat, T., Bhardwaj, S., Blaschke, S., & Labrique, A. (2018). Digital health vision: Could MomConnect provide a pragmatic starting point for achieving universal health coverage in South Africa and elsewhere? *BMJ Global Health*, *3*(Suppl 2), e000626. https://doi.org/10.1136/bmjgh-2017-000626

Mishra, Dr. S. B., & Alok, Dr. S. (2017). *HANDBOOK OF RESEARCH METHODOLOGY*.

Mogoba, P., Phillips, T. K., Myer, L., Ndlovu, L., Were, M. C., & Clouse, K. (2019). Smartphone usage and preferences among postpartum HIV-positive women in South Africa. *AIDS Care*, *31*(6), 723–729. https://doi.org/10.1080/09540121.2018.1563283

Moodley, J., Constant, D., Botha, M. H., van der Merwe, F. H., Edwards, A., & Momberg, M. (2019). Exploring the feasibility of using mobile phones to improve the management of clients with cervical cancer precursor lesions. *BMC Women's Health*, *19*(1), 2. https://doi.org/10.1186/s12905-018-0702-1

Mukaka, M. (2012). A guide to appropriate use of Correlation coefficient in medical research. *Malawi Medical Journal : The Journal of Medical Association of Malawi*, *24*(3), 69–71.

Nanjundeswaraswamy, D., & Divakara, S. (2021). DETERMINATION OF SAMPLE SIZE AND SAMPLING METHODS IN APPLIED RESEARCH. *Proceedings on Engineering Sciences*, *3*, 25–32. https://doi.org/10.24874/PES03.01.003

Nardi, P. M. (2018). *Doing Survey Research: A Guide to Quantitative Methods*. Routledge.

National-digital-strategy-for-south-africa-2019-2024-b.pdf. (n.d.). Retrieved September 19, 2021, from http://www.health.gov.za/wp-content/uploads/2020/11/national-digital-strategy-for-south-africa-2019-2024-b.pdf

Ndayizigamiye, P., Kante, M., & Shingwenyana, S. (2020). An adoption model of mHealth applications that promote physical activity. *Cogent Psychology*, *7*(1), 1764703. https://doi.org/10.1080/23311908.2020.1764703

Nguyen, B. (2017). *2.1 What is PCA? | Multivariate Statistical Analysis with R: PCA & Friends making a Hotdog*. https://bookdown.org/brian_nguyen0305/Multivariate_Statistical_Analysis_with_R/what-is-pca.html

Nsor-Anabiah, I. S., Udunwa, M. U., & Malathi, D. S. (2019). *Review of the Prospects and Challenges of mHealth Implementation in Developing Countries*. https://www.semanticscholar.org/paper/Review-of-the-Prospects-and-Challenges-of-mHealth-Nsor-Anabiah-Udunwa/619ab6bb8afda1c64bfe0bcb488008a52d3ad8b7

Nunes, A., Limpo, T., & Castro, S. L. (2019). Acceptance of Mobile Health Applications: Examining Key Determinants and Moderators. *Frontiers in Psychology*, *10*, 2791. https://doi.org/10.3389/fpsyg.2019.02791

Nurhayati, S., Anandari, D., & Ekowati, W. (2019). The Evaluation of Nutrition Information System Using Combined Method of Unified Theory of Acceptance and Usage of Technology (UTAUT) and Task Technology Fit (TTF). *IOP Conference Series: Earth and Environmental Science*, *255*(1), 012007. https://doi.org/10.1088/1755-1315/255/1/012007

Oates, B. (2005). *Researching Information Systems and Computing*.

O'Connor, Y., Andreev, P., & O'Reilly, P. (2020a). MHealth and perceived quality of care delivery: A conceptual model and validation. *BMC Medical Informatics and Decision Making*, *20*(1), 41. https://doi.org/10.1186/s12911-020-1049-8

O'Connor, Y., Andreev, P., & O'Reilly, P. (2020b). MHealth and perceived quality of care delivery: A conceptual model and validation. *BMC Medical Informatics and Decision Making*, *20*(1), 41. https://doi.org/10.1186/s12911-020-1049-8

Ojo, A. I. (2018). mHealth Interventions in South Africa: A Review. *SAGE Open*, *8*(1), 2158244018767223. https://doi.org/10.1177/2158244018767223

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. *International Journal of Information Management*, *34*(5), 689–703. https://doi.org/10.1016/j.ijinfomgt.2014.06.004

Omotayo, F. O., & Haliru, A. (2020). Perception of task-technology fit of digital library among undergraduates in selected universities in Nigeria. *The Journal of Academic Librarianship*, *46*(1), 102097. https://doi.org/10.1016/j.acalib.2019.102097

Osei, E., & Mashamba-Thompson, T. P. (2021). Mobile health applications for disease screening and treatment support in low-and middle-income countries: A narrative review. *Heliyon*, *7*(3), e06639. https://doi.org/10.1016/j.heliyon.2021.e06639

Pai, R. R., & Alathur, S. (2021). Bibliometric Analysis and Methodological Review of Mobile Health Services and Applications in India. *International Journal of Medical Informatics*, *145*, 104330. https://doi.org/10.1016/j.ijmedinf.2020.104330

Palas, J. U., Sorwar, G., Hoque, M. R., & Sivabalan, A. (2022). Factors influencing the elderly's adoption of mHealth: An empirical study using extended UTAUT2 model. *BMC Medical Informatics and Decision Making*, *22*(1), 191. https://doi.org/10.1186/s12911-022-01917-3

Park, J., Gunn, F., Lee, Y., & Shim, S. (2015). Consumer acceptance of a revolutionary technology-driven product: The role of adoption in the industrial design development. *Journal of Retailing and Consumer Services*, *26*, 115–124. https://doi.org/10.1016/j.jretconser.2015.05.003

Petersen, F., Jacobs, M., & Pather, S. (2020). *Barriers for User Acceptance of Mobile Health Applications for Diabetic Patients: Applying the UTAUT Model* (pp. 61–72). https://doi.org/10.1007/978-3-030-45002-1_6

Qudah, B., & Luetsch, K. (2019). The influence of mobile health applications on patient - healthcare provider relationships: A systematic, narrative review. *Patient Education and Counseling*, *102*(6), 1080–1089. https://doi.org/10.1016/j.pec.2019.01.021

Rahi, S. (2017). Research Design and Methods: A Systematic Review of Research Paradigms, Sampling Issues and Instruments Development. *Rahi S*, *6*(2), 6.

Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of things (IoTs) in smart farming in a typical Middle Eastern country within the context of Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technology in Society*, *63*, 101415. https://doi.org/10.1016/j.techsoc.2020.101415

Şahintürk, L., & Özcan, B. (2017, November 30). *The Comparison Of Hypothesis Tests Determining Normality and Similarity Of Samples*. https://www.semanticscholar.org/paper/The-Comparison-Of-Hypothesis-Tests-Determining-and-%C5%9Eahint%C3%BCrk-%C3%96zcan/de21fdaa0adab35eddbc1f42460aeb232ecfeb44

Said, G. R. E. (2022). Factors Affecting mHealth Technology Adoption in Developing Countries: The Case of Egypt. *Computers*, *12*(1), 9. https://doi.org/10.3390/computers12010009

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Khan, I. (2021a). Environmental air pollution management system: Predicting user adoption behavior of big data analytics. *Technology in Society*, *64*, 101473. https://doi.org/10.1016/j.techsoc.2020.101473

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Khan, I. (2021b). Environmental air pollution management system: Predicting user adoption behavior of big data analytics. *Technology in Society*, *64*, 101473. https://doi.org/10.1016/j.techsoc.2020.101473

Shiferaw, K. B., & Mehari, E. A. (2019). Modeling predictors of acceptance and use of electronic medical record system in a resource limited setting: Using modified UTAUT model. *Informatics in Medicine Unlocked*, *17*, 100182. https://doi.org/10.1016/j.imu.2019.100182

Shrestha, N. (2021a). Factor Analysis as a Tool for Survey Analysis. *American Journal of Applied Mathematics and Statistics*, *9*, 4–11. https://doi.org/10.12691/ajams-9-1-2

Shrestha, N. (2021b). Factor Analysis as a Tool for Survey Analysis. *American Journal of Applied Mathematics and Statistics*, *9*(1), Article 1. https://doi.org/10.12691/ajams-9-1-2

Swartz, A., LeFevre, A. E., Perera, S., Kinney, M. V., & George, A. S. (2021). Multiple pathways to scaling up and sustainability: An exploration of digital health solutions in South Africa. *Globalization and Health*, *17*(1), 77. https://doi.org/10.1186/s12992-021-00716-1

Taherdoost, H. (2022). *What are Different Research Approaches? Comprehensive Review of Qualitative, Quantitative, and Mixed Method Research, Their Applications, Types, and Limitations* (SSRN Scholarly Paper 4178694). https://papers.ssrn.com/abstract=4178694

Tam, C., & Oliveira, T. (2016). Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective. *Computers in Human Behavior*, *61*, 233–244. https://doi.org/10.1016/j.chb.2016.03.016

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. JSTOR. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157–178. JSTOR. https://doi.org/10.2307/41410412

Wahyuni, D. (2012). *The Research Design Maze: Understanding Paradigms, Cases, Methods and Methodologies* (SSRN Scholarly Paper ID 2103082). Social Science Research Network. https://papers.ssrn.com/abstract=2103082

Walliman, N. (2017). *Research Methods: The Basics : 2nd edition*. Routledge. https://doi.org/10.4324/9781315529011

Wallis, L., Blessing, P., Dalwai, M., & Shin, S. D. (2017). Integrating mHealth at point of care in low- and middle-income settings: The system perspective. *Global Health Action*, *10*(sup3), 1327686. https://doi.org/10.1080/16549716.2017.1327686

Wan, L., Xie, S., & Shu, A. (2020). Toward an Understanding of University Students' Continued Intention to Use MOOCs: When UTAUT Model Meets TTF Model. *SAGE Open*, *10*(3), 215824402094185. https://doi.org/10.1177/2158244020941858

Wang, H., Tao, D., Yu, N., & Qu, X. (2020a). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. *International Journal of Medical Informatics*, *139*, 104156. https://doi.org/10.1016/j.ijmedinf.2020.104156

Wang, H., Tao, D., Yu, N., & Qu, X. (2020b). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. *International Journal of Medical Informatics*, *139*, 104156. https://doi.org/10.1016/j.ijmedinf.2020.104156

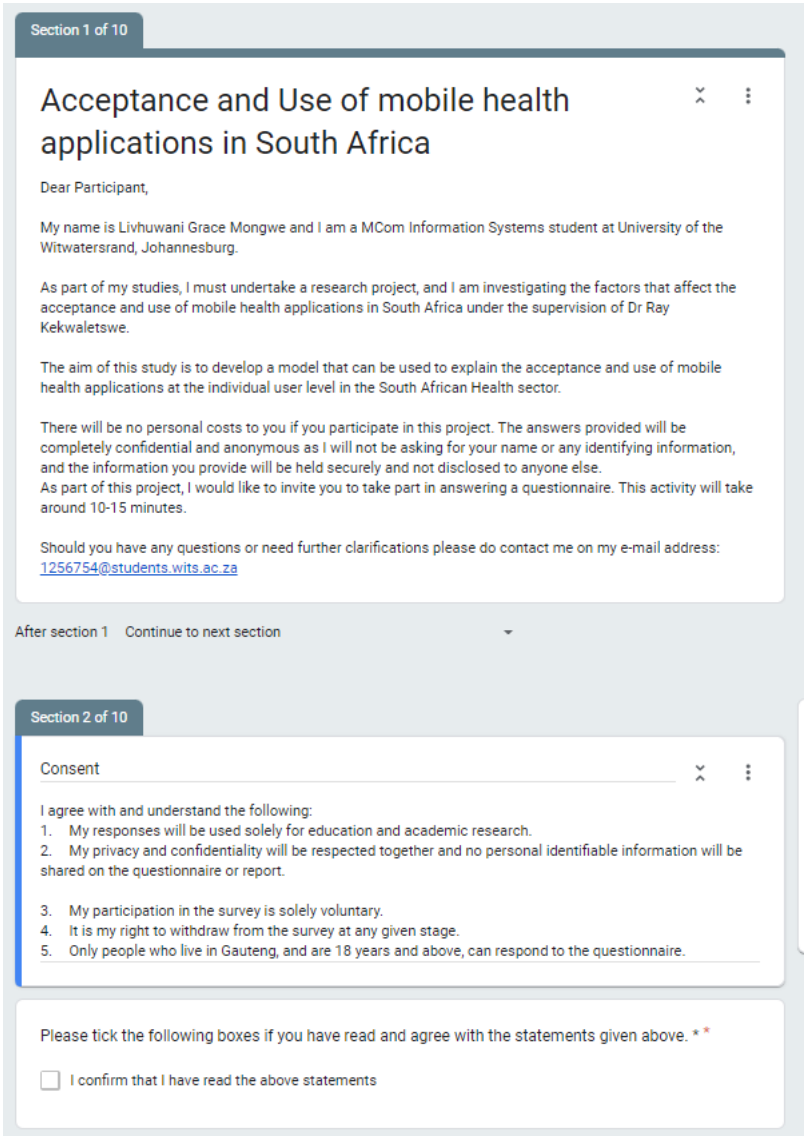
Yang, L., Yang, S. H., & Plotnick, L. (2013). How the internet of things technology enhances emergency response operations. *Technological Forecasting and Social Change*, *80*(9), 1854–1867. https://doi.org/10.1016/j.techfore.2012.07.011

Yu, Y., Yan, X., Zhang, xi, & Zhou, S. (2019, January 1). *What They Gain Depends on What They Do: An Exploratory Empirical Research on Effective Use of Mobile Healthcare Applications*. https://doi.org/10.24251/HICSS.2019.483

Zhou, T., Lu, Y., & Wang, B. (2010a). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, *26*(4), 760–767. https://doi.org/10.1016/j.chb.2010.01.013

Zhou, T., Lu, Y., & Wang, B. (2010b). Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, *26*(4), 760–767. https://doi.org/10.1016/j.chb.2010.01.013

Appendix A: Final Research Instrument



Section 1 of 10

Acceptance and Use of mobile health applications in South Africa

Dear Participant,

My name is Livhuwani Grace Mongwe and I am a MCom Information Systems student at University of the Witwatersrand, Johannesburg.

As part of my studies, I must undertake a research project, and I am investigating the factors that affect the acceptance and use of mobile health applications in South Africa under the supervision of Dr Ray Kekwaletswe.

The aim of this study is to develop a model that can be used to explain the acceptance and use of mobile health applications at the individual user level in the South African Health sector.

There will be no personal costs to you if you participate in this project. The answers provided will be completely confidential and anonymous as I will not be asking for your name or any identifying information, and the information you provide will be held securely and not disclosed to anyone else.
As part of this project, I would like to invite you to take part in answering a questionnaire. This activity will take around 10-15 minutes.

Should you have any questions or need further clarifications please do contact me on my e-mail address: 1256754@students.wits.ac.za

After section 1 Continue to next section

Section 2 of 10

Consent

I agree with and understand the following:
1. My responses will be used solely for education and academic research.
2. My privacy and confidentiality will be respected together and no personal identifiable information will be shared on the questionnaire or report.

3. My participation in the survey is solely voluntary.
4. It is my right to withdraw from the survey at any given stage.
5. Only people who live in Gauteng, and are 18 years and above, can respond to the questionnaire.

Please tick the following boxes if you have read and agree with the statements given above. * *

☐ I confirm that I have read the above statements

Section 3 of 10

Section A: Demographic Information

Description (optional)

Which age group do you belong to? *

- 18-30
- 31-40
- 41-50
- 51-60
- Older than 60

What is your gender ?

- Female
- Male

Level of education

- High School
- Diploma
- Bachelors Degree
- Post Graduate
- Other...

Occupation

- Employed
- Self-Employed
- Student
- Unemployed

Do you own a smartphone? *

- Yes
- No

Mobile Health Application defined

Mobile health application is defined as the use of technology to support health care services through the use of voice calls, SMS messaging systems, wireless transmission of data and mobile phone applications. Examples include reminders to encourage adherence to medication, Apps to for disease management, Apps to encourage healthy behavior, an App for contact tracing during the Covid-19 pandemic, healthy life Apps such as fitness trackers and diet Apps and health education Apps. The examples are not an exhaustive list.

Have you used a mobile health application? *

- Yes
- No

How often do you use the mobile health application *

- Always
- Sometimes
- Never

Section 4 of 10

Section B: Factors that affect the use and acceptance of mobile health applications

The questions in the next sections make use of a 7-point scale with the ratings described below:

1: Strongly disagree
2: Disagree
3: Slightly disagree
4: Neither agree or disagree
5: Somewhat disagree
6: Agree
7: Strongly agree

Task Characteristics

Description (optional)

I need to access my health-related information anytime anywhere *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I need to acquire my health-related information anywhere *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I need to know my health-related information anywhere *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Section 5 of 10

Section title (optional)

Description (optional)

Technology Characteristics

Description (optional)

Mobile health applications provide ubiquitous service *

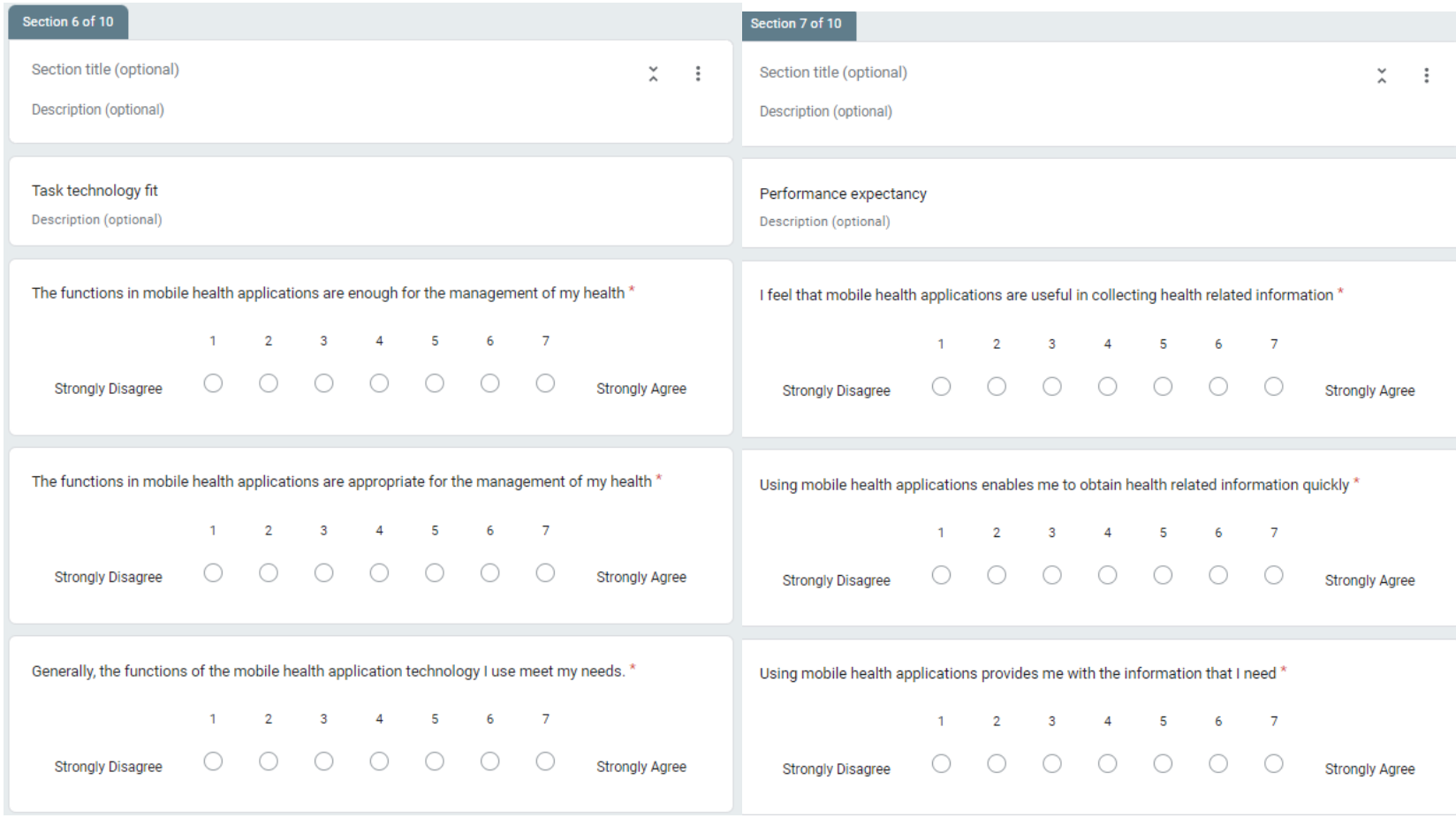
	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Mobile health applications provide real time services *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Mobile health applications provide services where my privacy is protected *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree



Section 6 of 10

Section title (optional)

Description (optional)

Task technology fit

Description (optional)

The functions in mobile health applications are enough for the management of my health *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

The functions in mobile health applications are appropriate for the management of my health *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Generally, the functions of the mobile health application technology I use meet my needs. *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Section 7 of 10

Section title (optional)

Description (optional)

Performance expectancy

Description (optional)

I feel that mobile health applications are useful in collecting health related information *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using mobile health applications enables me to obtain health related information quickly *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Using mobile health applications provides me with the information that I need *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Section 8 of 10

Section title (optional)

Description (optional)

Effort expectancy

Description (optional)

I can quickly and easily use a new technological tool *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I find using the mobile health application that I use easy *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I think learning to operate new technology is easy for me *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

My interaction with the mobile health application that I use is clear and understandable *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Section 9 of 10

Section title (optional)

Description (optional)

Facilitating conditions

Description (optional)

I have the necessary resources to use the mobile health application that I use *

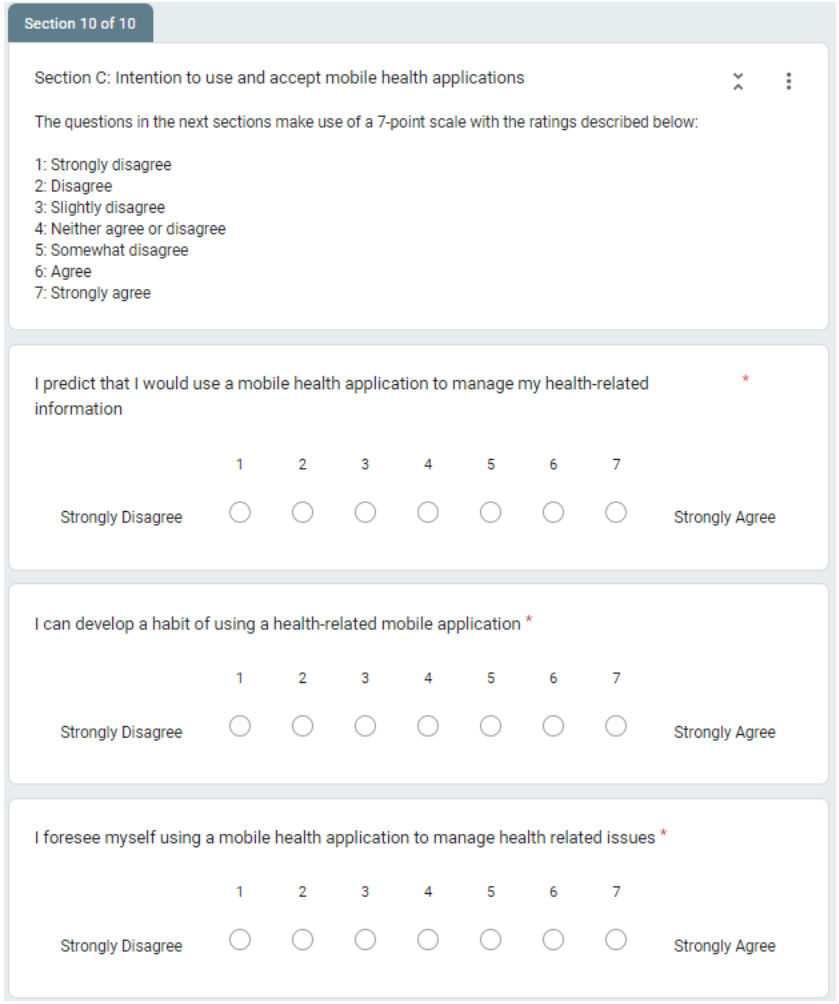
	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I have the necessary knowledge to use the mobile health application that I use *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Support is available if I struggle with a function of the mobile health application that I use *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree



Section 10 of 10

Section C: Intention to use and accept mobile health applications

The questions in the next sections make use of a 7-point scale with the ratings described below:

1: Strongly disagree
2: Disagree
3: Slightly disagree
4: Neither agree or disagree
5: Somewhat disagree
6: Agree
7: Strongly agree

I predict that I would use a mobile health application to manage my health-related information *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I can develop a habit of using a health-related mobile application *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

I foresee myself using a mobile health application to manage health related issues *

	1	2	3	4	5	6	7	
Strongly Disagree	○	○	○	○	○	○	○	Strongly Agree

Appendix B: Ethics Approval Certificate

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

SCHOOL OF BUSINESS SCIENCES ETHICS COMMITTEE
CONSTITUTED UNDER THE UNIVERSITY HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: CBUSE1963**
PROJECT TITLE	A model for the acceptance and use of mobile health applications in South Africa: A UTAUT and TTF perspective
INVESTIGATOR	Livhuwani Mongwe
SCHOOL/DEPARTMENT OF INVESTIGATOR	School of Business Sciences
DATE CONSIDERED	19 November 2021
DECISION OF THE COMMITTEE	Approved Unconditionally
RISK LEVEL	Low Risk
EXPIRY DATE	31 December 2023

ISSUE DATE OF CERTIFICATE 22 November 2021 **CHAIRPERSON** _____ (Neetu Ramsaroop)

cc: Supervisor: Prof Ray Kekwaletswe

DECLARATION OF INVESTIGATOR

To be completed in duplicate and **ONE COPY** returned to the Chairperson of the School/Department ethics committee.

I fully understand the conditions under which I am are authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee.

Xasetoa
Signature

Date 08 / 12 / 2021

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

Appendix C: Participation Letter

Dear Participant,

My name is Livhuwani Grace Mongwe and I am a MCom Information Systems by Course Work student at University of the Witwatersrand, Johannesburg.

As part of my studies, I must undertake a research project, and I am investigating the factors that affect the acceptance and use of mHealth applications in South Africa under the supervision of Dr Ray Kekwaletswe.

The aim of this study is to develop a model that can be used to explain the acceptance and use of mHealth applications at the individual user level in the South African Health sector.

There will be no personal costs to you if you participate in this project. The answers provided will be completely confidential and anonymous as I will not be asking for your name or any identifying information, and the information you give to me will be held securely and not disclosed to anyone else.

As part of this project, I would like to invite you to take part in answering a questionnaire. This activity will take around 15-20 minutes.

The survey link can be accessed below:

https://forms.gle/rPDQgAArAQebqK1p7

Should you have any questions or need further clarifications please do contact me on my e-mail address: 1256754@students.wits.ac.za

Kind Regards,
LG Mongwe

Appendix D: Turnitin Report

LG Mongwe_Research Report (Chapter 1 to 6)_29 March 2023-1.docx

ORIGINALITY REPORT

6%	6%	5%	0%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	wiredspace.wits.ac.za Internet Source	3%
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3	Tao Zhou, Yaobin Lu, Bin Wang. "Integrating TTF and UTAUT to explain mobile banking user adoption", Computers in Human Behavior, 2010 Publication	1%
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6	Vai, Carlos Tam Chuem. "Understanding the Individual Performance of M-Banking.", Universidade NOVA de Lisboa (Portugal), 2019 Publication	1%



30 March 2023