Factors Influencing mHealth Acceptance: An Empirical Investigation from a Trust-Anxiety Perspective

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Table of Contents

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List of Figures

List of Tables

Abstract

Mobile health (mHealth) is an emerging healthcare technology designed specifically for improving individuals’ quality of life. Despite mHealth purported benefits, its acceptance rates have fallen short of industry expectations. Lack of trust and anxiety have been identified as two long-term barriers to successful mHealth acceptance. Yet, little attention has been devoted to understand individuals’ acceptance of mHealth services from a trust and anxiety perspective in the current mHealth acceptance research. The virtuality of mHealth services and the sensitivity of health data are two major issues affecting individuals’ acceptance of mHealth services before the initial interaction stage with the service. In such situations, trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety become central parts of the acceptance decisions formed around the use of mHealth services. Motivated by this fact, this study develops a trust-anxiety model to understand individuals’ acceptance behavior of mHealth services. The developed model draws on innovation attributes (trialability, visibility, relative advantage, and ease of use), external and interpersonal social influence, and facilitating conditions from information systems, innovation diffusion, and social psychology research to understand the factors affecting individuals trust and anxiety when accepting mHealth services from social, technological, and behavioral dimensions.

The developed model was empirically validated via a sample of 385 potential adopters in Saudi Arabia and 507 in the United Kingdom using online self-administrated surveys. Partial least squares structural equation modeling was used to assess the developed research model. The findings in Saudi Arabia and the United Kingdom showed that potential adopters mHealth acceptance was largely promoted by their level of trust in mHealth service followed by their level of trust in mHealth service provider. The results further indicated that in the United Kingdom, mHealth use anxiety can significantly reduce potential adopters’ acceptance of mHealth services. Moreover, the results in Saudi Arabia and the United Kingdom showed that trialability can increase individuals mHealth use anxiety, while ease of use can significantly reduce it when accepting mHealth services. However, in Saudi Arabia, the results further showed that trust in mHealth service can significantly reduce potential adopters mHealth use anxiety when accepting mHealth services. The results also suggested that trust in mHealth service can be promoted by relative advantage, ease of use, interpersonal social influence, and trust in mHealth service provider in both countries before the initial interaction stage with the service. On the other hand, the results revealed that trust in mHealth service provider was positively affected by external social influence, relative advantage, facilitating conditions, and visibility in Saudi Arabia. However, in the United Kingdom, trust in mHealth service provider has been found to be positively associated with external social influence, facilitating conditions, and relative advantage.

From a theoretical perspective, this study contributes to existing mHealth acceptance literature by providing a comprehensive understanding of mHealth acceptance behavior from a trust-anxiety perspective. From a practical perspective, the study offers valuable information for mHealth participants that can help them in promoting their mHealth services acceptance rates.

Declaration

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

Copyright Statement

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Chapter 1: Introduction

1.1 Research Background

The rapid development of mobile communication technologies and networks has affected many facets of the service industry, including the expectations and demands of its consumers. One of the recently affected service sectors by such technological advances is the healthcare industry. With the increased demand for better healthcare quality, many players in the traditional healthcare market have altered their healthcare processes, including the way in which they engage with their consumers and deliver their services (Zhoa et al., 2018). The popularity of mobile devices has greatly contributed to such a transformation to take place in the healthcare industry (Faiola, Papautsky, and Isola, 2018). Mobile devices, such as smartphones, tablets, and wearable devices, have made it possible for healthcare service providers to offer innovative services through mobile terminals, such as mHealth.

mHealth is a personalized interactive service that involves the use of mobile devices in medicine and public health (Dicianno et al., 2015). In its early stages, mHealth technology were specifically designed to assist healthcare professionals in decision-making and emergency care. As mHealth has been widely adopted in the healthcare industry, it has been then extended to the healthcare at-distance market to provide the public with medical services electronically via mobile devices. The term "healthcare at-distance market" refers to a segment of the healthcare industry that involves the delivery of traditional healthcare services like consultations, diagnostics, treatment, and monitoring services to patients at distance. Nowadays, mHealth apps are one of the recent developments of mHealth technologies enabled by the exponential growth of smartphone and tablet user base (Dicianno et al., 2015).

A typical mHealth service use environment usually consists of a mHealth service provider, patients, and mHealth technology. It is worth noting that in the mHealth service use environment, a mHealth service provider is more of an abstract entity representing various units involved in the development, delivery, and support of mHealth services, which usually include health care organizations (public/private hospitals or clinics), healthcare professionals (doctors, therapists, nurses), and third-party partners (e.g., mHealth app software developers and customer service centers). With mHealth services, individuals are no longer tied to a healthcare service provider's geographical location, and citizens of one country traveling nationally and internationally can still have access to their local healthcare provider's services. Existing mHealth studies demonstrate the great potential benefits mHealth can offer to both individuals and healthcare service providers alike in terms of reduced healthcare costs, improved treatment outcomes, and efficient healthcare processes (Guo et al., 2016; Hoque and Sorwar, 2017; Zhao et al., 2017).

While the benefits of mHealth services are obviously evident, the acceptance rates of these services remain low among their potential adopters, and some of these apps are not even successfully operating in the existing healthcare at a distance market (Labrique et al., 2013; Munyua et al., 2015). For example, recent statistics show that the number of mHealth apps in major application stores, such as the Apple App and Google Play stores, has decreased by 20% from 2021 to 2022 (Ceci, 2022). Since the success of these services depends primarily on their massive acceptance by their intended adopters, service providers need to understand potential adopters mHealth acceptance behavior in order to promote the acceptance rates of their services. mHealth acceptance behavior mainly concentrates on understanding the key factors underlying individuals' behavior when accepting mHealth services for the first time.

mHealth is a unique phenomenon (Zhu et al., 2018) that challenges the traditional view of healthcare practices, including the way in which medical diagnoses, consultations, treatments, and medication are conducted. These apps are specifically designed to shift the power from healthcare providers to patients in order to improve their quality of life. As an emergent innovation, uncertainties still characterize the use of mHealth apps for managing one's health. Particularly in the absence of direct use experience, individuals become uncertain about mHealth service performance in terms of its functionality and reliability, especially as mHealth apps performance depends greatly on the processing capability and network connectivity of the smartphones and tablets used in receiving these services (Yang et al., 2014).

In addition to the uncertainties surrounding mHealth service performance, individuals may also become uncertain about mHealth service provider's behavior. Such uncertainty may emerge from one's concern about being physically harmed by service provider actions. A concern that cannot be ignored in the light of recent reports about medical errors in the traditional healthcare services sector. According to Cheraghi-Sohi et al. (2021) and Elliott et al. (2018) studies, around 237 million medication errors and over 58% of diagnosis errors occur yearly during a local doctor general practices (GP) consultation, both of which have caused severe harmful effects or deaths to patients. As mHealth services represent a new innovative channel for receiving health services that are directly related to a person's health and even life/death matters (Zhu et al., 2018), individuals may question mHealth service provider's ability to provide reliable healthcare services and information over mobile terminals.

Furthermore, the uncertainties surrounding mHealth service use environment in terms of its mHealth service provider's behavior make mHealth technology fertile ground for mHealth use anxiety to flourish when accepting mHealth services. Such anxiety is largely triggered by the fears of losing one's information confidentiality when using mHealth services. As noted earlier, mHealth services are interactive personalized services in which their functions (e.g., health tracking, self-diagnosis, consultation features) depend primarily on the information individuals disclose to mHealth service providers over mHealth platforms. Specifically, to use mHealth services, individuals must first grant access requests to their personal information, like their current geolocation, health information, and lifestyle activities, which are necessary for mHealth services main functions to operate. However, not all of these permission requests are for operational purposes. Some access requests are for the purpose of generating revenue by selling patients data to third parties, thereby causing potential adopters to become more concerned about the information being collected, the accuracy of that information, and with whom it is being shared (Schnall et al., 2015; Harrison et al., 2016). Recent reports on the available mHealth app market are a good demonstration of this kind of service provider's opportunistic behavior. According to Tangari et al. (2021), the majority of mHealth apps available on the market have a code that shares users collected data with unauthorized third parties like research companies and 23% of these data transmissions have taken place on insecure communication protocols. Accordingly, this indicates that unless mHealth potential adopters can overcome their uncertainties regarding the attributes, motives, and prospective actions of others on whom they rely in a transaction, these uncertainties may act as a barrier to individuals' acceptance decisions of mHealth services (Kramer, 1999).

1.2 Research Problem

One of the foci for researchers in information systems (IS) field since the development of IS artifacts is to understand individuals' acceptance behavior of innovative technologies (Davis et al., 1998; Venkatesh et al., 2003; Rogers, 1996). Like other IS artifacts, mHealth services have attracted researchers' interest as it struggles to find a widespread acceptance among its adopters while being in its infancy stages (Cocosilla, 2013; Guo et al., 2016; Guo et al., 2013; Fox et al., 2018; Meng et al., 2021; Hoque and Sorwasr, 2017; Dwived et al., 2016). mHealth acceptance means the extent to which individuals intend to use mHealth services, which represents the initial step toward their usage and full adoption (Ajzen et al., 1990; Rogers, 2014).

In attempt to understand individuals acceptance of mHealth services, the majority of earlier mHealth studies have relied on traditional IS acceptance and use models, such as Protection Motivation Theory (Guo et al., 2015; Fox et al., 2018), Technology Acceptance Model (Guo et al., 2013; Rajak et al., 2021), Unified Technology Acceptance and Use Theory (Hoque and Sorwasr, 2017; Dwived et al., 2016), Motivation Model (Cocosilla, 2013; Meng et al., 2021) and Theory of Planned Behavior (Deng et al., 2014) as the basis of their investigation. Some researchers, on the other hand, have based their studies on the privacy-personalization (Guo et al., 2016), cognitive and affective attitude (Wang et al., 2018), and consumer value (Lee and Han, 2015) literature to gain further insights into the factors influencing individuals' intention to use mHealth services. These mHealth studies generally predict individuals' acceptance of mHealth services based on the cognitive beliefs and affective attitudes formed around the technology (e.g., perceived ease of use, performance expectancy, perceived risks, facilitating conditions) or one's health (e.g., perceived severity, perceived vulnerability), except for the motivation model.

Yet, individuals' acceptance of mHealth services may not be solely influenced by cognitive and attitudinal factors since emotions are also an integral part of individuals' acceptance of new technologies (Gratch and Marsella, 2004; Lazarus and Folkman, 1984; Loewenstein et al., 2001; Beaudry and Pinsonneault, 2010). Drawing on motivation model, earlier evidence suggests that individual's mHealth acceptance was to a great extent affected by their emotional responses (Lui et al., 2019; Cocosila, 2013; Meng et al., 2021). The motivation model assumes that individuals' acceptance of new technologies is a function of two motivational factors, namely, perceived usefulness, a cognitive belief, and perceived enjoyment, a positive emotional reaction (Ryan and Deci, 2000). However, given that in mHealth app adoption contexts, the acceptance of mHealth services mainly takes place before individuals initial interaction stage with the services. In such a stage, therefore, individuals' mHealth use intention is less likely to be dominated by positive emotional responses like perceived enjoyment.

Mainly, the adoption process of mHealth apps consists of three stages based on an individual's interaction level with the service: the pre-initial interaction stage, the initial interaction stage, and the continuous interaction stage. The pre-initial interaction stage is the stage in which individuals form their acceptance of mHealth services based on their indirect experience with the service (Li et al., 2022). Once individuals have accepted the use of mHealth services, the next stage is the initial interaction stage in which individuals put mHealth apps into actual use and start to form their intentions toward making transactions with mHealth service provider based on their initial direct experience with the service. On the other hand, the continuous interaction stage occurs when individuals reinforce their previous acceptance decisions of mHealth services based on their direct use experience with the service (Li et al., 2022). Accordingly, before the initial interaction stage with mHealth services, individuals acceptance of mHealth services is more likely to be influenced by negative emotional responses like anxiety due to the increased uncertainties surrounding mHealth use environment in terms of its performance and its service provider's behavior.

While the effect of negative emotional responses, such as anxiety, on individuals' acceptance of mHealth services has been recognized by prior research (Deng et al., 2014; Guo et al., 2013; Rajak et al., 2021; Hoque and Sorwasr, 2017), anxiety in existing mHealth acceptance studies has primarily been focused on individuals' technology anxiety, which is a generic anxiety factor reflecting the fears individuals develop as a negative emotional reaction to their ability to use mHealth services as a technological tool in general. However, as noted earlier, the anticipated privacy threats surrounding mHealth service use environment may lead individuals to develop other negative emotional reactions, such as mHealth use anxiety. Such an anxiety factor is associated with the fears individuals develop in terms of the loss of their information confidentiality when using mHealth services.

An anxiety factor like mHealth use anxiety becomes critical in personalized service settings such as mHealth services before the initial interaction stage with the service as individuals have to exchange their personal and health information with mHealth service providers over mobile terminals. This may suggest that in the pre-initial interaction stage with the service, mHealth use anxiety may negatively affect potential adopters' acceptance of mHealth services, particularly in the light of the increased reports about mHealth app service providers information privacy violations. Accordingly, to leverage mHealth acceptance rates, mHealth service providers must first mitigate individuals mHealth use anxiety. However, less is understood about the role mHealth use anxiety plays in mHealth use intention. Therefore, this research is motivated to fill in this gap by examining the extent to which mHealth use anxiety as a contextual anxiety factor related to mHealth services affects individuals mHealth use intention and goes a step further by investigating the factors affecting it before the initial interaction stage with the service.

On the other hand, trust has been suggested as a key cognitive belief promoting individuals acceptance of mHealth services (Fox et al., 2018; Guo et al., 2016). It is commonly believed by prior IS researchers that trust is a multidimensional factor, and that there are at least two trustees in whom users develop their trust in when accepting innovative mobile services like mHealth, namely, the technology itself and its service provider (Siau and Shen, 2003; McKnight et al., 2002; McKnight et al., 2010). Trust in technology reflects individuals' beliefs in technology reliability, that the technology will operate properly and consistently, and functionality, that the technology has the necessary features to complete the required tasks (Thatcher et al., 2013). On the other hand, trust in service provider reflects individuals' beliefs in service provider's competence, the ability to do what the trustor need, benevolence, to act in the trustor's best interest, and integrity, the degree of service provider's honesty and promise-keeping (Gefen et al., 2003).

While the importance of trust in mHealth service and trust in mHealth service provider on mHealth use intention have been recognized by earlier researchers (Deng et al., 2018; Meng et al., 2018), their join effect on individuals mHealth use intention and the factors underlying their development remain largely unexplored in the current mHealth acceptance literature (Fox et al., 2018). This gap is further compounded when studying the factors promoting individuals trust in mHealth service and trust in mHealth service provider from social and behavioral aspects.

Existing studies on trust in mHealth acceptance research is mostly focused on the factors promoting individuals trust in mHealth service or its service provider from technological, institutional, and personal dimensions (Deng et al., 2018; Meng et al., 2018). Given that individuals trust in mHealth service and its service provider before the initial interaction stage with the service is primarily driven by first impression cues and available second-hand information, relying solely on technological, institutional, and personal factors may not be sufficient for understanding individuals trust promoters in mHealth acceptance research. Prior research in social psychology, psychology, and information systems fields have long recognized the critical role social influence factors like interpersonal social influence and external social influence and behavioral factors like facilitating conditions play in the formation process of individuals' cognitive beliefs (Deutsch and Gerard, 1955; Kaleman, 1958; Venkatesh et al., 2001). However, less attention has been given to the factors affecting individuals trust in mHealth acceptance research from social and behavioral aspects. As such, more research is required to fill in this gap to gain a better understanding of the factors affecting individuals' trust in mHealth service and trust in mHealth service provider when accepting mHealth services.

Accordingly, this research proposes a theoretical model that explains potential adopters' acceptance of mHealth services from a trust-anxiety perspective. Such a perspective is used for three reasons. First, it is believed by many IS scholars that the adoption behavior of new technologies on the individual level is more likely to combine cognitive and emotional factors in its early stages (Ferreira et al., 2014; Komiak and Benbasat, 2006; Beaudry and Pinsonneault, 2010). This is due to the dual role individuals play in online service environments as both IS users and service customers (Komiak and Benbasat, 2006; Gefen et al., 2003). At many consumptions situations at the customer level, individuals decisions are largely driven by the effective reactions and cognitive beliefs formed around the technology (Komiak and Benbasat, 2006; Ferreira et al., 2014). This is even more the case within mHealth app adoption contexts in which individuals' acceptance decisions occur in an environment where they cannot directly experience mHealth services without first downloading and configuring mHealth apps on their smartphone or tablet devices. In such settings, the initial emotional reactions and cognitive beliefs formed around mHealth services become an integral part of potential adopters acceptance decisions of mHealth service.

Second, the spatial separation between mHealth service providers and customers makes mHealth services users more likely to be exposed to service provider's opportunistic behaviors. The recent studies conducted on available mHealth apps in the market are a good demonstration of this kind of behavior. According to a study conducted on over 200 mHealth apps available on major online apps stores that 88% of these apps had included a code that shared users collected data with unauthorized third parties (e.g., research companies), and that 23 % of these data transmissions has taken place on insecure communication protocols (Tangari et al., 2021). Such service providers opportunistic behaviors can evoke potential adopters' negative emotional response like mHealth use anxiety when considering the acceptance of mHealth services for the first time.

Third, trust becomes important in situations whenever dependency and vulnerability among exchange parties exist (Wang et al., 2005). This is mainly the case with mHealth services, in which individuals' health decisions depend primarily on the information and services provided to them at a distance by mHealth service providers via mobile terminals. The mediated nature of mHealth services increases potential adopters' uncertainty about mHealth services performance and its mHealth service provider behavior, especially as inaccurate assessments, poor recommendations, and inconsistent mHealth functioning can render them vulnerable to faultily decisions. In such situations, trust, as a subjective cognitive belief, helps potential adopters to overcome their uncertainties and anticipated risks by subjectivity rolling out undesired yet possible future actions/behaviors of those upon whom they rely on when using mHealth services (Gefen et al., 2003). Accordingly, trust is considered in this research as the key cognitive belief affecting individuals acceptance of mHealth services (Deng et al., 2018; Meng et al., 2018; Fox et al., 2018).

To this end, this research uses a trust-anxiety centered lens to study potential adopters' acceptance of mHealth services. The proposed research model draws its theoretical foundation on the Stimulus-Organism-Response (SOR) model since it provides a comprehensive lens for organizing the proposed research model and answering the research questions. In contrast to traditional IS acceptance and use theories and attitudinal models, SOR posits that cues (stimuli) from the behavioral environment can exert influence on individuals internal state (organism), which in turn influences their behavioral intentions/actions (reactions) (Mehrabian and Russell, 1974). Stimuli are influencing variables from the external environment that influence an individual’s internal cognitive and emotional state (Liu et al., 2018; Loh et al., 2022). Given that in mHealth apps context individuals cannot directly experience mHealth services until they have downloaded and figured mHealth apps on their mobile devices. In such a stage, individuals’ trust in Health service, trust in mHealth service provider, and mHealth use anxiety are more likely to be affected by the external influencers around them. Accordingly, this research utilizes innovation attributes, interpersonal and external social influence, and facilitating conditions from innovation diffusion, IS, social psychology, and psychology research as predictors of individuals trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety from social, technological, and behavioral dimensions.

1.3 Research Aim and Objectives

The main aim of this study is to provide a comprehensive understanding of potential adopters’ acceptance of mHealth services from a trust-anxiety perspective. To achieve this aim, this research seeks to develop a theoretical model that can predict the key factors influencing potential adopters trust in mHealth service provider, trust in mHealth service, and mHealth use anxiety before their initial interaction stage with mHealth service and goes a step further by examining the effect of trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety on mHealth use intention. To meet this aim, the following specific objectives are developed:

- To identify the role trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety play in mHealth acceptance.
- To identify the factors affecting potential adopter trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety before the initial interaction stage with mHealth service from innovation diffusion theory, facilitating conditions, and social influence research.
- To propose a theoretical model that investigates mHealth acceptance behavior from a trust-anxiety perspective.

- To validate the proposed model by conducting a comparative empirical study between the United Kingdom and Saudi Arabia potential adopters.
- To create a theoretical model that can predict mHealth acceptance behavior from a trust-anxiety perspective.

1.4 Research Questions

Based on the research problem identified in section 1.2, the following research questions have been developed to gain a better understanding of potential adopters' acceptance behavior of mHealth services from a trust-anxiety perspective:

1. What are the key factors affecting potential adopters trust in mHealth services and their service providers before the initial interaction stage with mHealth service?
2. What are the key factors affecting potential adopters mHealth use anxiety when accepting mHealth services?
3. To what extent do trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety affect potential adopters' acceptance of mHealth services?

1.5 Geographical Scope of The Research

This research choses Saudi Arabia and The United Kingdom as its geographical scope for validating the proposed research model for the following reasons. First, while the number of mobile devices holders and internet subscribers are high in Saudi Arabia and the United Kingdoms, the adoption rates of mHealth services are still slow. As shown in Table 1.1, statistics shows that the percentage of smart phone and tablet holders in Saudi Arabia is 91% and 36% respectively, while the number of internet subscribers is around 30 million individuals from the whole population (GlobaWenInedx report, 2020; Statista, 2020). A similar situation can be seen in the United Kingdom (UK). For example, the percentage of UK smartphone holders is 92%, while the percentage of table holders is 56% (GlobaWenInedx report, 2020). On the other hand, the number of internet subscribers in the UK is 62 million individuals (Statista, 2020). As the statistics show, both countries have the required resources for using mHealth indicating that mHealth potential adopters are ready to accept mHealth services.

Table 1.1 Mobile Devices Holders and Internet Subscribers in Saudi Arabia and United Kingdom

	Saudi Arabia	**United Kingdoms**
Papulation	35 million	67 million
Smartphone	91%	92%
Tablets	36%	56%
Internet Subscribers	30 million	62 million

Sources: Saudi General Authority for Statistics, 2020; GlobaWenInedx report, 2020; and Statista, 2020

On the market level, the ministry of health in Saudi Arabia has provided their residents with a range of mHealth apps that are available through major application stores, such as medical appointment booking apps (e.g., Mawid), medical records apps (e.g., Sehhaty), and medical emergency services apps (e.g., Asafny). In addition to self-service apps, the ministry of health has also provided its residents with several free medical apps that connect patients with registered physicians to provide them with real-time virtual consultation and medication services, such as Sehha and Eyadty. The Saudi mHealth market, also, provides its residents with a wide range of paid healthcare services, such as Cura, Nahdicare Clinics, Altibbi, and Dr. Sulaiman Al-Habib apps. A similar situation can be seen in the United Kingdom's mHealth market. In the UK, the National Health Service department has provided its residents with several mHealth apps, such as medical appointment apps (e.g., the NHS app), prescription ordering apps (e.g., My GP and Well Repeat NHS prescriptions), self-diagnosing apps (e.g., ASK NHS), and medical apps (e.g., Babylon, Push Doctors, and Patient Access Point apps). Despite mHealth market readiness in both countries, current statistics show that the adoption rates of mHealth services remain low in these two countries. For example, the Saudi National Digital Transformation Report shows that the number of Mawid app users has increased slowly from 9.8 million users in 2019 to 15 million users in 2020, while the number of Sehha users has increased from 668,000 users in 2019 to 1.6 million users in 2020 (Saudi General Authority for Statistics, 2020). Similarly, the UK National Health Service department statistics show that the number of NHS app downloads has increased from 209,000 downloads in 2019 to 1.3 million downloads in 2020 (UK National Health Service Department, 2020). Accordingly, the slow adoption rates of mHealth services in these two countries fit with the research context and aim.

Second, Saudi Arabia and the United Kingdom significantly differ in terms of their national cultures, which enable the researcher to gain further insights into potential adopters' mHealth acceptance patterns. National culture refers to "the collective programming of the mind that distinguishes one group or category of people from another." (Hofstede, 1993, p. 89). Hofstede's four dimensions of culture offer the most widely used and appropriate conceptual classification of national culture. These dimensions assess countries' cultural differences on the following four elements: individualism/collectivism, power distance, masculinity/femininity, and uncertainty avoidance, as shown in Table 1.2. Among these dimensions, uncertainty avoidance and individualism/collectivism are the most suitable dimensions to differentiate between Saudi Arabia and United Kingdom mHealth users in this study. This is because individualism/collectivism affects the way individuals behave and take their decisions, while uncertainty avoidance affects the way new individuals shape their trust beliefs and mHealth use anxiety emotion. Hofstede has described Saudi Arabia as a collectivist culture with high levels of uncertainty avoidance. On the other hand, United Kingdom has been described as an individualism culture with low levels of uncertainty avoidance, as shown in Table 1.2. Such cultural differences can significantly reflect on the way individuals' responses to their environment (Hofstede, 2001), including the way in which they form their trust beliefs, mHealth use anxiety emotion, and mHealth acceptance behaviors. Therefore, to understand mHealth acceptance behavior, it is important to explore the phenomenon from countries with different cultural values to gain further insights into individuals' mHealth acceptance behavior.

Table 1.2 Cultural Differences Between Saudi Arabia and the United Kingdom

Culture Dimensions	Definition	Saudi Arabia	United Kingdom
Individualism/Collectivism	The degree to which people in a country prefer to act as individuals rather than as members of groups.	Collectivism	Individualism
Power Distance	The degree of inequality among people that the population of a country considers as normal: from relatively equal (that is, a small power distance) to extremely unequal (a large power distance).	High	Low
Masculinity/Femininity	The degree to which people in a country prefer structured over unstructured situations.	Moderate	High
Uncertainty Avoidance	The degree to which tough values like assertiveness, performance, success, and competition, which in nearly all societies are associated with the role of men, prevail over tender values like the quality of life, maintaining warm personal relationships, service, caring for the weak, and solidarity, which in nearly all societies are more associated with women's roles.	High	Low

Source: Hofstede (1980; 2001)

Third, the literature review shows that less research has been conducted in Saudi Arabia and the United Kingdom contexts. For example, earlier research has studied individuals mHealth acceptance behavior in Bangladesh (Hoque and Sorwasr 2017), Canada and the United States (Dwived et al., 2016; Fox et al., 2018), and China (Deng et al., 2013; Guo et al., 2016), while studies in Saudi Arabia and the United Kingdom context remain scarce in the current literature. Testing the proposed research model in eastern countries such as Saudi Arabia and western countries such as the United Kingdom can provide a rich understanding of potential adopters acceptance behavior of mHealth services from a trust-anxiety perspective. This is due to the differing settings of data protection laws and information and communication technology infrastructures between the countries, which may affect individuals' acceptance patterns of mHealth services (Rose and Straub, 1998). Therefore, to fill in this gap, this research conducts a cross-country analysis by studying potential adopters mHealth acceptance behavior in Saudi Arabia and the United Kingdom.

1.6 Research Methodology

In order to meet the research aims and answer its research questions, this study uses quantitative research under the guidance of positivism paradigm. Particularly, this study adopts online self-administered surveys as its main data collection method. The survey was developed based on existing literature to preserve content validity, which was initially developed in English and was then translated to Arabic after being pilot tested. The pilot study was primarily used to test the validity and reliability of the measurement scales used in this study. Based on the results of the pilot study, items with high cross loadings were revised to improve their clarity and to increase their discriminant validity. Once the questionnaire items were improved, the online self-administered surveys were distributed to research participants in Saudi Arabia and the United Kingdoms to collect research data. From the 1st of June to the 31st of July 2021, this study has collected a total of 427 completed responses in Saudi Arabia and 553 responses in the United Kingdom. After removing problematic responses (e.g., outliers), a total of 385 responses in Saudi Arabia and 507 responses in the United Kingdom (UK) were used for testing the research proposed model. The collected research data has been then analyzed using partial least square equation modeling (PLS-SEM). A two-stage approach was adapted to conduct PLS-SEM analysis as recommended by Hair et al., (2017). In the first stage, the measurement model using confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of latent variables. In the second stage, the structural model was tested to examine the hypotheses relationship among the proposed latent variables.

1.7 Research Significance

This research makes several original theoretical contributions to mHealth acceptance research. First, different from previous mHealth acceptance studies that focuses on cognitive-affective attitude, privacy-personalization paradox, consumer value, and traditional IS acceptance and use models (Meng et al., 2021; Houqe et al., 2018; Fox et al., 2018; Lee and Han, 2015; Wang et al., 2018; Guo et al., 2016) to explain individuals' acceptance of mHealth services, this study explores individuals' mHealth acceptance from a trust-anxiety perspective. As mHealth represents a novel service for most of its potential adopters, it is more likely that its potential adopters' mHealth use intention will be dominated by cognitive beliefs and negative emotional reactions like trust and anxiety when accepting mHealth services. This is particularly due to the increased uncertainties surrounding mHealth service provider's behavior and its mHealth service performance before the initial interactions stage with the service. While previous mHealth acceptance studies have generally recognized the effect that trust and anxiety factors, such as technology anxiety, can play in individuals' mHealth use intentions (Houqe et al., 2018; Fox et al., 2018; Guo et al., 2016), less attention has been devoted to understand individuals acceptance of mHealth services from a trust-anxiety perspective. Accordingly, this study builds on previous trust and anxiety investigations in mHealth acceptance research and extends it in two ways. First, it extends prior trust investigations by differentiating between individuals' trust in mHealth service and their trust in mHealth service provider and examining their combined effect on mHealth use intention. Second, it extends prior anxiety investigations by incorporating mHealth use anxiety as a contextual anxiety factor related to mHealth settings and examining its negative effects on mHealth use intention. The empirical findings in this study identify trust in mHealth service as one of the leading factors promoting potential adopters' acceptance of mHealth services followed by trust in mHealth service provider in Saudi Arabia and The United Kingdom. On the other hand, the results identify mHealth use anxiety as a significant factor decreasing individuals' acceptance of mHealth services in the United Kingdom. Accordingly, this research enriches the existing body of knowledge in mHealth acceptance literature by examining individuals' mHealth use intention from a trust-anxiety perspective.

Second, while previous IS acceptance research has long recognized the dynamic nature of individual anxiety as an emotional reaction (Thatcher and Perrew, 2002; Marakas et al., 2000), the factors affecting potential adopters' anxiety when accepting mHealth services remain largely unexplored in the existing mHealth acceptance literature. This research, therefore, fills in this gap by exploring the role trialability and ease of use from innovation diffusion theory and trust in mHealth service from a trust perspective play in mHealth use anxiety. The findings in Saudi Arabia and The United Kingdom underline the dynamic nature of individuals anxiety before the initial interaction stage with the service and depict trialability as an mHealth use anxiety promoter while ease of use as inhibitor in Saudi Arabia and the United Kingdom. It further discovers that trust in mHealth service can significantly mitigate individuals mHealth use anxiety in the United Kingdom when accepting mHealth services. To the author's best knowledge, this is the first study to investigate the factors affecting individuals' anxiety in mHealth acceptance research. Accordingly, this research advances the current state of knowledge about the dynamic nature of individuals anxiety in mHealth acceptance research and opens a new path for future research in the literature to explore the factors affecting individuals' anxiety when accepting mHealth services.

Third, while the factors affecting potential adopters' trust in mHealth services and its service providers have gained increased attention in mHealth acceptance research, less consideration has been given to the factors promoting individual trust from social and behavioral aspects. Furthermore, although the importance of technological factors has been acknowledged by earlier mHealth trust research, these technological factors have been primarily investigated from the traditional IS acceptance and use models perspective (e.g., Unified Technology Acceptance and Use Theory and Technology Acceptance Model). As far as this research has found, none of the existing mHealth trust studies have investigated mHealth attributes from the Innovation Diffusion Theory (IDT). Unlike traditional IS acceptance and use models, which assume that mHealth trust is primarily a function of two technological attributes (e.g., perceived ease of use, perceived usefulness), IDT provides a rich set of technological attributes (e.g., visibility and relative advantages) that have been found to play a critical role in developing individuals' trust in mHealth services and its mHealth service providers in mHealth acceptance research.

Accordingly, this research is believed to extend the relevant literature on trust in mHealth acceptance research.

To this end, this research contributes to mHealth acceptance literature by providing a comprehensive understanding of individuals mHealth acceptance behavior from a trust-anxiety perspective. Such contributions may also contribute to the general IS acceptance and online trust literature in two ways. First, this research contributes to the general IS acceptance research by highlighting the importance of contextual factors like mHealth use anxiety in the acceptance behavior of new personalized technologies. Such a factor becomes critical in contexts in which information confidentiality becomes an issue when accepting the use of the new personalized technology. Accordingly, this research is believed to respond to the call in IS research to embrace context when investigating individuals' acceptance and use of technology artifacts (Orlikowski & Iacono, 2001; Venkatesh et al., 2011). Second, this research contributes to the online trust literature by highlighting the role behavioral factors such as facilitating conditions and informative social influence factors such as external social influence play in the development process of individuals online trust before their initial interaction stage with the technology. Such factors have received less attention in online trust research in the pre-initial interaction stage with online services, as seen in Table 2.3 in Section 3.2.3. Therefore, the proposed research model can serve as a strong reference for future research to understand potential adopters' acceptance behavior of innovative personalized technologies like mHealth.

1.8 Structure of the Thesis

This thesis consists of seven chapter. Figure 1.1 presents the organization of this thesis. In chapter one, the research background and the major problems (research gaps) detected on mHealth acceptance literature are introduced. On this basis, the research aim, objectives, and question are explained. This chapter further discusses the geographical scope used to validate the proposed research model. This chapter also highlights the significance of this research in terms of its theoretical contribution to mHealth acceptance research.

Chapter 2 elaborates on the research gaps presented in mHealth acceptance literature. It starts by defining the concept of mHealth and critically reviewing the existing research on mHealth acceptance literature. Findings of mHealth acceptance literature review facilitated the identification of the relevant factors contributing to mHealth use intention, which serves as the foundation of the proposed research model. Based on the review of mHealth acceptance research, the concepts of trust and anxiety is critically reviewed and discussed in the existing mHealth acceptance literature to identify the gaps in the current mHealth acceptance research from a trust-anxiety perspective. This chapter ends by elaborating on the concepts and theories underlying the development of the proposed research model for this study.

In Chapter 3, the development of the 18 hypotheses for this research is presented. The model is developed based on the literature review presented in Chapter 2. The aim of the model is to explain potential adopters mHealth acceptance behavior from a trust-anxiety perspective.

Chapter 4 is used to explain the research methodology used to answer the research developed questions and achieve its aim in detail. This chapter starts by presenting the research philosophy, the data collection method, and data analysis method adopted to validate the proposed model. The scale of measurement, sampling unit, and the sample size used to test the research model are also discussed in this chapter.

Chapter 5 presents the data analysis and results. This chapter focuses on the empirical analysis of the collected data from Saudi Arabia and the United Kingdom. It starts by presenting the results of the pilot study and further elaborates on its revised instruments. It then presents the analysis results of the full-scale data collected from Saudi Arabia and the United Kingdom samples. It starts first with cleaning the collected data and presenting its descriptive analysis. Next, the sample data from Saudi Arabia and the United Kingdom are tested using partial least square equation modelling.

Chapter 6 presents the discussion and the findings of this research. The hypothesized testing results are discussed in detail. The chapter also discusses some of the original and important findings regarding the key factors affecting potential adopters trust in mHealth, trust in mHealth service provider, and mHealth use anxiety during mHealth acceptance behavior. The chapter also discusses the similarity and difference between previous research findings and this research findings.

Chapter 7 presents the theoretical contribution, practical implication, research limitations, and it concludes by providing suggestions for future research.

Figure 1.1 Thesis Structure

Chapter 2: Literature Review

This chapter provides an overview of the current research on mHealth acceptance area. The purpose of this review is to provide a comprehensive understanding of the current research on trust and anxiety in mHealth acceptance research to identify the gaps in the existing literature. To accomplish the aforementioned purpose, the chapter starts by providing an overview of mHealth acceptance research. It then discusses the concept of trust and the factors contributing to its development in mHealth acceptance research. The chapter also discusses the concept of anxiety in mHealth acceptance research to establish the importance of mHealth use anxiety. The chapter then discusses the concepts and theories underlying the development of the proposed research model for this study and ends up by providing a summary of the research gaps in the current mHealth acceptance literature.

2.1 An Overview of mHealth Acceptance Research

2.1.1 Mobile Health Definition

The review of the literature shows that the concept of mobile health (mHealth) has attracted various definitions and descriptions. The concept of mHealth was first coined by Istepanian and Pattichis in 2002, in which it was described as an emerging mobile communication and network technology for healthcare. Once mHealth had been widely adopted by the healthcare industry, it was defined by the Worldwide Health Organization (WHO) as a medical and public health practice supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants (PDAs), sensors, and other wireless devices, that aid in decision making and emergency care (WHO, 2011).

As mHealth entered the healthcare at distance industry, it has been defined as an emerging subset form of electronic healthcare technologies (eHealth) that delivers timely and ubiquitous health related information and services via portable devices, such as smartphones, tablets, wearable technologies, patient monitoring devices, personal computers, and PADs (Guo et al., 2016;

Könsgen et al., 2017; Kallander et al., 2013). Some researchers, such as Akter et al. (2013), however have regarded mHealth as a new paradigm that distinctly differs from the concept of eHealth due to the unique characteristics characterizing mHealth services, such as their ubiquity, mobility, accessibility and instant connectivity. Accordingly, mHealth was defined by Akter et al. (2013) as a personalized and interactive healthcare service that provides its users with universal access to health-related services through mobile platforms.

It seems from earlier definitions that "mHealth" is more of an umbrella term covering the areas of mobile devices, networking, and healthcare provision (Deng et al., 2014). Given the dynamic nature of mHealth markets and the abstract nature of previous mHealth definitions in the field, this research therefore needs to further clarify the exact mobile devices that can serve as mHealth service devices. Free et al. (2010) indicate that not all mobile devices are qualified for providing mHealth services, such as personal computers (PCs), since they are constrained by available wireless network connections. On the other hand, Istepanian and Woodward (2016) have excluded PADs from the definition of mHealth services since they are one of the less widely used mobile devices nowadays. Alternatively, Alam et al. (2020) have identified smartphones and tablets as the key drivers of mHealth services supported by economical mobile internet subscriptions.

With the growing base of smartphone and tablet owners and the advances in information and communication technologies, various healthcare players in the market have provided their health services electronically via mobile health applications known as mHealth apps. Hussain et al. (2018) defined mHealth apps as a software program that delivers health-related services through smartphones and tablets. Nowadays, smartphones and tablets are easily accessible and offer unique processing powers that allow complex apps, such as those that provide remote medical services, to run in different geographical locations, including rural and urban areas. While wearable and self-tracking devices can be leveraged by almost all individuals with internet access, these types of mobile devices are specifically designed for the purpose of tracking one’s health and they are not as widespread and accessible as mHealth apps on smartphones and tablets. Balapour et al. (2019) indicate that mHealth apps remain the most accessible form of affordable mHealth services for the general population and they can even be used for tracking one’s health status (e.g., blood pressure and weight) through self-reported features. Therefore, this research selects mHealth app as the chosen mHealth service for this study and accordingly define it as a healthcare application that connects patients with service providers via smartphones and tablets to deliver real-time personalized healthcare services, such as monitoring, consultation, medication, and health information services.

2.1.2 Stages of mHealth Adoption and mHealth Acceptance

Research in mHealth adoption area has long recognized the multi-phase nature of individuals use of mHealth services. This can be seen when looking at mHealth adoption literature in that there are many phases of an individual's use of mHealth technology, ranging from the pre-initial use phase (Guo et al., 2016; Meng et al., 2021; Fox et al., 2018), the initial use phase (Cao et al., 2020; Lui et al., 2022; Alam et al., 2020), the continuous use phase (Akter and D'Ambra, 2013; Yousaf et al., 2021; Tandon et al., 2023), to the habitual and attachment use phase (Li et al., 2020; Xiaofei et al., 2021; Rasul et al., 2023). This focus on different phases of mHealth use has shown that individuals' adoption of mHealth technology can significantly differ based on their progression state with the technology (Li et al., 2022).

Roger's (1983) innovation decision process from the innovation diffusion theory is one of the central theoretical models used in understanding individuals' adoption of new technologies in IS acceptance and use research (Agarwal and Prasad, 1998; Cooper and Zmud, 1990; Kwon and Zmud, 1987; Moore and Benbasat, 1991). According to Rogers (2014), the adoption of an innovation consists of a series of interrelated activities that start by gaining initial knowledge of the innovation (known as the knowledge stage), form an attitude toward the innovation (known as the persuasion stage), make a decision to accept or reject the innovation (known as the decision stage), implement the innovation (known as the implementation stage), and end by reinforcing previously made acceptance (or rejection) decisions about the adoption of the innovation (known as the confirmation stage). Furthermore, Rogers indicates that the acceptance (or rejection) of an innovation does not occur until the decision stage, indicating that the decision, implementation, and conformation stages represent three different periods of an individual's adoption of an innovation. Particularly, the decision stage is the stage in which individuals form their first intention toward the use of the innovation (Olesen et al., 2021). Once an individual has formed their use intention, the next stage is the implementation stage. In this stage, individuals put the new innovation into actual use (Karahanna et al., 1999). On the other hand, the confirmation stage is the stage in which individuals reinforce their previous acceptance decisions to decide whether to continue to use the innovation or discontinue it (Rogers, 2014).

The stages of decision, implementation, and conformation in the innovation decision process align with the multi-phases view of mHealth use. Specifically, in mHealth app adoption environments, the decision stage usually occurs before an individual's initial interaction with the technology (Li et al., 2022). Such a stage in mHealth adoption research is in line with the pre-initial use phase. A phase in which individuals form their intentions toward the use of mHealth services for the first time based on indirect experience with the service (Li et al., 2022). In such a stage, individuals rely on their general perceptions about mHealth technology, such as mHealth use experience, mHealth service provider expected behavior, mHealth service expected technical attributes, and mHealth use outcomes and consequences, based on their previous experience with similar technologies or their general perceptions of new technologies use experience (Venkatesh et al., 2001). On the other hand, the implementation stage usually takes place once individuals have accepted the use of mHealth services (Roger, 2014). Such a stage in mHealth app adoption environments involves the initial use of the technology, which usually consists of trial and exploration activities of mHealth’s main functions and services. Accordingly, such a stage in mHealth adoption research aligns with the concept of the initial use phase. In such a phase, individuals tend to form their intentions to make transactions with mHealth services that involve risk-taking actions (e.g., willingness to share health information, intention to follow a recommended medical advice/s, intention to purchase medical services, etc.) based on their initial direct experience with the service. Furthermore, the confirmation stage usually occurs at the point in which individuals have used the system and reinforce their previously made adoption decisions based on their direct use experience of the service (Yousaf et al., 2021; Li et al., 2022). Such a stage in mHealth app adoption environments is more likely to line up with the continuous, habitual, and attachment use phases in which individuals generally form their continuous intentions toward the use of mHealth services in mHealth adoption research.

For the purpose of this study, this research differentiates between three stages in an individual's adoption process of mHealth services based on their interaction level with the service: the pre-initial interaction stage, the initial interaction stage, and the continuous interaction stage. The pre-initial interaction stage is used to reflect the stage in which individuals' acceptance of mHealth services occurs. On the other hand, the initial interaction stage is used to reflect the stage in which individuals' initial use of mHealth services occurs, while the continuous interaction stage is used to reflect the stage in which continuous use of mHealth services occurs.

Given that mHealth services are relatively new technologies with low acceptance rates, the main focus of this research is thus placed on the pre-initial interaction stage to understand individuals' acceptance of mHealth services. Such a stage in the adoption process of mHealth services represents the initial step toward understanding individuals use and full adoption of mHealth services.

2.1.3 Factors Affecting mHealth Acceptance

Understanding what makes potential adopters accept innovative mobile services like mHealth is a challenging task that requires the study of customer behavior. The study of customer behavior mainly concentrates on understanding the key factors underlying individuals' behavior when deciding to buy/use certain products and services to satisfy their needs and desires (Blackwell et al., 2006).

It is believed by many behavioral and traditional IS acceptance and use theories at the individual level that customers behavioral intention usually leads to their actual behavior (Fishbein and Ajzen, 1975; Ajzen, 1991; Davis et al., 1989; Venkatesh et al., 2003). Accordingly, behavior intention has been extensively used by earlier behavioral and IS researchers as the main predictor of an individual's actual behavior. Hence, when one refers to technology acceptance in IS acceptance and use research, this implies the behavioral intention to use it (Venkatesh et al., 2003, Szajna, 1996; Yousafzai et al., 2010).

A closer look at mHealth acceptance literature shows that in attempt to understand potential adopters acceptance of mHealth services, the majority of earlier researchers have relied on traditional information systems (IS) acceptance and use models, such as the Protection Motivation Theory (Guo et al., 2015; Fox et al., 2018), Technology Acceptance Model (Guo et al., 2013; Rajak et al., 2021), Unified Technology Acceptance and Use Theory (Hoque and Sorwasr, 2017; Dwived et al., 2016), Theory of Planned Behavior (Deng et al., 2014), and

Motivation Model (Cocosila, 2013; Meng et al., 2021) as the basis of their investigation to examine whether the theoretical constructs of these models are also likely to influence potential adopters acceptance of mHealth services. Table 2.1 shows the main assumptions and the key factors underlying these theories. Some researchers, on the other hand, have drawn on privacy-personalization (Guo et al., 2016), customer value (Lee and Han, 2015), and cognitive and attitude (Wang et al., 2018) literature to gain further insights of the factors forming individuals' acceptance of mHealth technology.

Table 2.1 Traditional IS Acceptance Models

Theory	Assumptions	Core Constructs	Definitions
Protection Motivation Theory	The theory assumes that individuals are motivated to engage in protective behaviors when they feel threatened in a risky situation. The theory postulates that an individual's behavioral intention to engage in protective behavior is a function of two cognitive processes known as threat and coping appraisals (Rogers, 1975; Maddux and Rogers, 1983). Threat appraisal generally relates to an individual's assessment of the risk degree adverse consequences posed by a threating event, while coping appraisal relates to one's capacity to deal with and avoid that threatening event. In PMT, threat appraisal consists of two factors, namely perceived vulnerability and perceived severity, while coping appraisal usually consists of response efficacy and self-efficacy perceptions.	Perceived Vulnerability	The extent to which an individual believes that one is likely to experience a relevant health threat (Rogers, 1975)
		Perceived Severity	The degree to which an individual believes that he/she will suffer from the consequences of that threat if it actually occurs (Rogers, 1975)
		Response Efficacy	The degree to which an individual believes that the induced response will be effective in alleviating the potential threat (Rogers, 1975)
		Self-Efficacy	The degree to which an individual believes in his/her ability to perform the recommended response (Rogers, 1975)
Theory of Planned Behavior	The theory presumes that an individual's behavioral intention is primarily a	Attitude	The degree to which a person has a favorable/unfavorable evaluation toward the behavior in question (Fishbein and Ajzen, 1975)

	function of three factors: attitude, subjective norms, and behavioral control.	Subjective Norms	The degree to which a person believes that most people important to him/her think that he/she should or should not perform the behavior in question (Fishbein and Ajzen, 1975)
		Behavioral Control	The degree to which a person believes in the ease or difficulty of performing the targeted behavior in question (Fishbein and Ajzen, 1975)
		Perceived Ease of Use	The degree to which a person believes that the use of the new system would not require a lot of effort (Davis, 1989)
Technology Acceptance Model	The theory assumes that an individual's behavioral intention to use a new technology is primarily a function of two cognitive factors: perceived usefulness and perceived ease of use (Davis et al., 1989)	Perceived Usefulness	The degree to which a person believes that the use of the new system would enhance his/her job performance (Davis, 1989)
Unified Technology Acceptance and Use Theory	The theory depicts an individual's IS use intention as a function of four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003)	Effort Expectancy	Similar to perceived ease of use in TAM
		Performance Expectancy	Similar to perceived usefulness in TAM
		Social Influence	Similar to subjective norms in TBP
		Facilitating Conditions	The degree to which an individual believes that the needed resources and support are available to perform the behavior in question, such as knowledge, resources, and skills (Venkatesh et al., 2012)
Motivation Model	The theory depicts an individual's behavioral intention as a function of extrinsic and intrinsic motivation.	Intrinsic Motivation	The perception that the user wants to perform the activity of using the system for no apparent reinforcement other than the process of performing the activity itself per sec" (Ryan and Deci, 2000)
		Extrinsic Motivation	The perception that a user will want to perform an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself" (Ryan and Deci, 2000).

In the following sections, previous studies in mHealth acceptance literature will be discussed in further detail to identify the salient factors underlying potential adopters' mHealth use intention. These studies are categorized based on the theories based on which they have been drawn from to understand potential adopters acceptance of mHealth services.

1. Protection Motivation Theory (PMT)

By drawing on PMT, the study of Guo et al. (2015) has investigated the factors affecting individuals' attitude when accepting mHealth services in China from a health protection perspective by incorporating the moderating role of individuals age and gender. In their study, Guo et al. (2015) noted that individuals' mHealth use intention was to a great extent affected by their attitudes, which was further determined by perceived severity, perceived vulnerability, response efficacy, and self-efficacy. The study further noted that the effect of perceived severity and perceived vulnerability on individuals' attitude was stronger among women and the elderly, while the effect of response efficacy and self-efficacy on attitude was stronger among men and the young. Unlike Guo et al. (2015), the study of Fox et al. (2016) has utilized PMT from a privacy perspective as it provides a flexible lens for exploring the competing impact of threat and coping appraisals from a health information privacy point of view on individuals mHealth use intention. In the study of Fox et al. (2018), PMT was used to understand the interplay between individuals' health information privacy concerns (a threat appraisal), risk beliefs (a threat appraisal), and trust beliefs (a coping appraisal) on individuals' acceptance of mHealth services. The study has further extended its model by including perceived ability that consisted of information seeking experience and mHealth self-efficacy from Social Cognitive Theory to gain further insights of the salient factors forming elderly mHealth use intention in Ireland and the United States. The results of Fox et al. (2018) study suggested that individuals mHealth acceptance was to a great extent associated with an individual's perceived ability, trust, and health information privacy concerns, while perceived risk has affected individuals' acceptance of mHealth service indirectly by increasing their health information privacy concerns. Among these factors, Fox et al. (2018) have noted the critical role trust played in potential adopters' mHealth acceptance decisions, thereby calling for further research that looks into the underlying mechanisms forming individuals' trust in mHealth context, particularly before their initial interaction stage with the service.

2. Theory of Planed Behavior (TBP)

In mHealth acceptance research, the study of Zhang et al. (2019) has built an integrative model by utilizing TBP and extending it with individual health differences (personal health status and personal health value) and health protection factors from PMT to examine individuals' acceptance of mHealth services in China. The results of Zhang et al. (2019) indicated that an individual mHealth use intention is a function of personal health status, personal health value, subjective norms, attitude, and self-efficacy. The study has further indicated that an individual's attitude in the early stages of the mHealth adoption process was to a great extent influenced by perceived severity, perceived vulnerability, response efficacy, and self-efficacy perceptions. In a similar vein, the study of Deng et al. (2014) has built its mHealth acceptance model by integrating TBP with perceived value and aging characteristics, which consisted of perceived physical conditions, resistance to change, technology anxiety, and self-actualization needs to compare middle-aged and senior citizens' mHealth acceptance behavior in China. The results of Deng et al. (2014) study revealed that for middle-aged mHealth potential adopters, mHealth use intention was negatively influenced by resistance to change and positively influenced by perceived value, attitude, and perceived behavioral control. On the other hand, for elderly mHealth potential adopters, the results showed that mHealth use intention was to a great extent negatively associated with technology anxiety while positively associated with individuals' self-actualization needs, attitude, perceived value, and perceived behavioral control.

3. Technology Acceptance Model (TAM)

TAM was utilized by Rajak et al. (2021) in which it was extended by attitude, social influence, technology anxiety, trust, perceived risk, perceived physical conditions, and resistance to change to investigate the factors underlying individuals mHealth acceptance behavior in India. Rajak et al. (2021) found a significant relationship between perceived ease of use, perceived usefulness, attitude, perceived risk, social influence, resistance to change, perceived physical conditions, and an individual's mHealth use intention. The study further showed that technology anxiety, trust, and social influence have affected individuals' acceptance of mHealth services indirectly by impacting their ease of use and usefulness perceptions. Apart from Rajak et al. (2021) study, TAM was also utilized by Guo et al. (2013) study in which it was extended by resistance to change, disposition to resistance to change, and technology anxiety to explore the enablers and inhibitors of mHealth acceptance among the elderly in China. The results of Guo et al. (2013) showed a strong positive correlation between perceived ease of use, perceived usefulness, and mHealth use intention. It further showed that individuals mHealth acceptance was to a great extent indirectly affected by individuals' disposition to resistance to change, technology anxiety, and resistance to change by affecting their mHealth ease of use and usefulness perceptions when accepting mHealth services.

4. Unified Technology Acceptance and Use Theory (UTAUT)

To understand potential adopter's acceptance and use behavior of mHealth services in Bangladesh, the study of Houqe et al. (2017) has integrated UATUT with resistance to change and technology anxiety as two aging characteristics affecting mHealth use intention among the elderly. Houqe et al. (2017) results showed a strong negative relationship between an individual's technology anxiety, resistance to change, and his/her mHealth use intention. The results further indicated that only performance expectancy, effort expectancy, and social influence from UTAUT has been found to be strongly associated with an individual mHealth use intention. Unlike the study of Houqe et al. (2017), the study of Dviewed et al. (2016) has utilized UTAUT2 model and extended it with waiting time and self-concept from a channel preference perspective to compare the factors predicting individuals' acceptance of mHealth services in the United States, Bangladesh, and Canada. The results demonstrated that in the United States and

Canada, mHealth use intention was significantly correlated with performance expectancy, effort expectancy, facilitating conditions, price value, social influence, self-concept, and waiting time. While in Bangladesh, mHealth use intention has been found to positively correlate with performance expectancy, effort expectancy, facilitating conditions, price value, social influence, hedonic motivation, and waiting time.

5. Motivation Model (MM)

In an attempt to predict individuals' acceptance of mHealth services in the United Kingdom, the study of Cocosila (2013) has drawn its theoretical investigations on the notions of MM and integrated them with individuals' attitude toward the activity and perceived risk theory. The results of Cocosila (2013) suggested a strong positive relationship between an individual's intrinsic and extrinsic motivation and their mHealth use intention, while an individual's attitude toward the activity has been found to affect an individual's mHealth use intention indirectly by negatively affecting an individual's perceived risk. On the other hand, perceived risk has been found to negatively affect mHealth use intention when accepting mHealth services.

The MM has also been utilized by the study of Meng et al. (2021), in which it has been integrated with mHealth service matching and mHealth source creditability from the Elaboration Likelihood Model and negative health mood to gain further understanding of the factors affecting individuals' intrinsic and extrinsic motivation when accepting mHealth services for the first time in China. The results revealed a strong positive link between an individual's intrinsic motivation, extrinsic motivation, and mHealth use intention. The results further suggested that an individual's intrinsic motivation is positively affected by mHealth service matching, while an individual's extrinsic motivation is positively affected by an individual's negative health mood, mHealth service matching, and mHealth source credibility.

6. Other Theoretical Models

Several mHealth researchers have developed their mHealth acceptance model based on cognitive-affective attitude, customer value, and privacy-personalization literature. From an attitude point of view, Wang et al. (2018) have differentiated between cognitive and affective attitudes and further investigated the factors contributing to their development from a service characteristics perspective in China. Their findings suggested that mHealth use intention is a function of individuals cognitive and affective attitudes, which were positively affected by two service characteristics: mHealth service matching and mHealth service competence. Their findings further suggested that service relevance can strengthen the effect of cognitive attitude on individuals mHealth use intentions while weakening the effect of affective attitude on mHealth use intentions. On the other hand, the study of Lee and Han (2015) investigated individuals mHealth acceptance behavior from a customer value perspective, in which they found a strong positive relationship between mHealth use intention, usefulness value, convenience value, and monetary value in China. On the other hand, the study of Guo et al. (2016) has developed an integrated model based on the privacy-paradox paradigm, trust, and age differences to empirically investigate individuals' acceptance of mHealth services from a technological and trust perspective. The results revealed that privacy concerns had negatively affected individuals mHealth use intention, while trust and perceived personalization had positively affected mHealth use intention. Further, the study indicated that the effect of personalization and privacy concerns on trust and mHealth use intention was stronger among young people. The study further showed that trust has not only promoted mHealth use intention but also helped balance the privacy-personalization paradox during the acceptance process of mHealth services for both the young and elderly potential adopters.

Based on the review of previous research in mHealth acceptance literature, it seems from earlier findings that mHealth use intention can be affected by various factors, which can be broadly categorized into cognitive (e.g., perceived risks, perceived usefulness, trust, perceived value, and facilitating conditions), attitudinal (e.g., cognitive attitude and affective attitude), affective (negative health mood), and emotional (perceived enjoyment and technology anxiety) aspects. While traditional IS acceptance models have shed light on the key factors affecting individuals mHealth acceptance decisions, mixed support has been provided to some of the core constructs underlying these theories, such as facilitating conditions and subjective norms (Houqe et al., 2017; Zhang et al., 2017; Dviewed et al., 2016). This suggests that traditional IS acceptance and use models are not adequate for understanding potential adopters mHealth acceptance behavior, which highlights the need to explore other factors (Fox et al., 2018). This is because traditional IS acceptance and use models, such as MM, UTAUT, TAM, TBP, and PMT, were originally developed for understanding organization employees work-related technology acceptance behavior (Komiak and Benbasat, 2005), a context in which a new technology use intention is more likely to be dominated by cognitive, attitudinal, and positive emotional factors. Yet, unlike generic work technologies, mHealth services are personalized technologies that operate primarily on the personal information individuals disclose to service providers over mobile networks. Such a type of technology, therefore, might be associated with a different set of technology acceptance factors than those associated with generic work technologies, which highlight the need to shift the focus from traditional IS acceptance models to models that are more relevant to mHealth context. A view that is also supported by Venkatesh et al. (2012) in IS field. Venkatesh et al. (2012) indicate that "theories that focus on a specific context and identify relevant predictors and mechanisms are vital in providing a rich understanding of a focal phenomenon" (p. 158). Therefore, a context-specific mHealth acceptance model is required to gain a better understanding of individuals acceptance behavior of mHealth services.

Drawing on previous findings from mHealth acceptance literature, a growing body of evidence has highlighted the importance of factors such as trust, from a cognitive aspect, and anxiety, from a negative emotional aspect, in individuals mHealth use intentions. For example, the literature showed a consistent positive relationship between trust and mHealth use intention in the studies of Guo et al. (2016) and Fox et al. (2018). A similar situation can be seen with anxiety. For instance, greater levels of technology anxiety have been found to correlate with lower levels of mHealth use intention in the studies of Deng et al. (2014) and Houqe et al. (2017). This indicates that an individual’s acceptance of mHealth services before the initial interaction stage with the service can be a function of trust and anxiety factors. However, despite the accumulation of supporting evidence, individuals’ mHealth acceptance behavior has rarely been investigated from a trust and anxiety perspective.

In the absence of firsthand experience, trust and anxiety become fundamental aspects of individuals mHealth acceptance decisions. It is believed by many IS acceptance researchers that the effect of anxiety on behavioral intention is stronger when potential adopters mentally consider the use of the new innovations for the first time (Nabih et al., 1997; Rogers, 2003). Such effects may even become stronger in mobile environments, particularly before individuals' initial interaction stage with the service, as people find transactions made using mobile devices to be less secure and more vulnerable to information loss than traditional means of service (Bailey et al., 2017; Gao et al., 2015). In such situations, trust becomes vital in forming individuals mHealth use intentions as it can minimize the potential risks associated with information disclosure and the uncertainties associated with mHealth service provider behavior and its technology performance (Fox et al., 2018; Guo et al., 2016). According to Wang et al. (2005), the general climate of trust can create an environment in which consumers will feel more at ease disclosing their sensitive information, service providers will feel more confident in conducting their services online, and there will be intensive interactions, transactions, and associations that will benefit customers and service providers alike. Accordingly, to better understand potential adopters acceptance of mHealth services, there is a need to understand potential adopters mHealth acceptance behavior from a trust-anxiety perspective.

2.2 Trust in mHealth Acceptance Research

2.2.1 What is Trust?

The concept of trust has existed long before the development of information communication technologies and mobile services, and it can be traced back to the Greek ancient era in which it was studied in an attempt to draw a picture of the human nature (Bailey, 2002). Just like the Greek philosophers, trust has attracted research interest from various disciplines, including psychology, sociology, management, information systems, and marketing, leading to the introduction of various definitions and conceptualizations that illustrate and describe trust in business and social relationships. This is due to the abstract and multi-dimensional nature of trust, which made it difficult for earlier researchers to operationalize what exactly trust is in human interactions even from the same discipline (Wang and Emurian, 2005; Li et al., 2008). Therefore, to better understand the nature of trust in mHealth context, it is worthwhile to first examine its definitions and conceptualization from the disciplines that have investigated it since each discipline has approached trust from a different point of view.

- In psychology, trust has been studied from an interpersonal relationship perspective in which it has been defined as a psychological belief reflecting the "expectancy held by individuals or groups that the word, promise, verbal, or written statement of another can be relied on" (Rotter, 1967, p. 651).
- In sociology, trust has been studied at the societal level, focusing on groups' collective psychological beliefs rather than the individual one. Unlike psychologists, sociologists have viewed trust as a multidimensional concept composed of cognitive, emotional, and behavioral dimensions (Lewicki et al., 1995). Cognitive trust reflects trustor's subjective judgement and expectation of trustee's future behavior, while emotional trust reflects the emotional state of the trustor when relying on the trustee (Beatty et al., 2011). On the other hand, behavioral trust reflects all trust-related actions that stream from emotional and cognitive trust dimensions, which include an element of risk-taking, such as one's willingness to rely on others, sharing personal information, and placing a transaction (Lewis and Weigert, 1985).
- In management, trust has been studied from either an organization-organization, organization-employees, or organizational-co-employees relationship perspective. Although trust in management has been investigated from the organizational level, it is believed that such view is still relevant to the customer trust context since trust in organizations and in individuals are somewhat correlated (Zaheer et al., 1998). In management, trust has been defined in various ways ranging from "perceptions about others' attributes and a related willingness to become vulnerable to others." (Rousseau et al., 1998, p. 394), "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995, p. 172) to an individual's belief about the extent to which the trusted party is likely to behave in a way that is 'benevolent, competent, honest, [and] predictable' (McKnight et al., 1998).
- In marketing, trust has been studied from a buyer-seller relationship perspective in which it has defined in different ways. For example, trust has been defined by Moorman,

Deshpande, and Zaltman as ‘‘a willingness to rely on an exchange partner in whom one has confidence in’’ (Moorman, Deshpande, and Zaltman, 1993, p. 90). It has also been defined by Morgan and Hunt (1994) as one’s confidence in an exchange party reliability and integrity, while it has been defined by Anderson and Weitz as “one party’s belief that its needs will be fulfilled in the future by the actions undertaken by the other party” (Anderson and Weitz, 1989, p. 312).

- In information systems, trust has been studied from a consumer-technology relationships perspective. Just as marketers and management researchers, trust in information systems has been defined in different ways. For example, trust has been defined as a cognitive belief reflecting trustor’s rational expectations of trustee behavior in that it will behave in a socially accepted manner to fulfil trustor needs (Gefen et al., 2003; Song et al., 2007; McKnight et al., 2002). It also has been defined by Gefen (2000) as the willingness to make oneself vulnerable to the actions taken by another based on one’s feelings of confidence and assurance. In addition, Ba and Pavlou (2002) have defined trust as “the subjective assessment of one party that another party will perform a particular transaction according to his or her confidant expectation, in an environment characterized by uncertainty” (p. 245).

As it can be noted from the majority of previous definitions, trust can be conceptualized either as a behavioral trust reflecting "one’s willingness to rely on or make oneself vulnerable to another" or as a cognitive trust reflecting "one’s positive expectation in another’s attributes." While both streams of definitions are relevant to mHealth acceptance context, the second stream of definition seems more related to mHealth acceptance behavior. This is because, according to Akhter et al. (2013), trust as an expectational belief already captures the willingness to be vulnerable to another in its conceptualization since people are not willing to rely on others unless they believe in their trustworthiness. In other words, it is believed by many researchers that behavioral trust is an essential part of cognitive trust since one cannot label an object of trust as trustworthy unless one is willing to take actions that entail risks (Morgen and Hunt, 1994). Accordingly, this research conceptualizes trust as a subjective cognitive belief reflecting one’s expectations of trustee attributes that are believed to be beneficial for the trustor.

In line with earlier researchers in the information systems field, this thesis further differentiates between potential adopters' trust in mHealth service and their trust in mHealth service provider. Information systems researchers have long believed that trust in service provider (e.g., the entity that provides the service) and trust in technology (e.g., the channel through which the service is provided) are two silent aspects of trust in online contexts (Siau and Shen, 2003; Komiak and Benbasat, 2004; Thatcher et al., 2013). Although mHealth services are viewed as "social actors" (Nass, Steuer, and Tauber, 1994), these objects of trust cannot perform violation acts (e.g., selling users' personal data to commercial companies or giving access to an authorized user) without the intervention of service providers' actions (Beldad and Hegner, 2018). Accordingly, online customers may build their trust in mHealth service using a different set of expectations than those used with mHealth service provider (Thatcher et al., 2013). Therefore, as shown in Table 3.1, this research defines trust in mHealth service as the degree to which an individual believes in the reliability and functionality of mHealth services, while trust in mHealth service provider is defined as the extent to which an individual believes in a service provider's competence, benevolence, and integrity (Thatcher et al., 2013; Gefen et al., 2003).

Table 2.2 Trust Dimensions

Entity of Trust	Trust Believes	Definition	Resource
Service Provider	Competence	Trustee ability to do what the trustor needs.	Gefen et al. (2003)
	Benevolence	The believe that the trustee will act in trustor's best interests.	
	Integrity	Trustee honesty and promise keeping.	
Technology	Reliability	The believe that the technology will operate properly and consistently.	Thatcher et al. (2013)
	Functionality	The believe that the technology will have the necessary features to complete the required tasks.	

2.2.2 Trust in the Early Stages of mHealth Acceptance

It is believed by many IS researchers that trust building mechanisms differ based on the interaction stage with the service (Kim, 2012; McKnight et al., 2004; Gefen et al., 2003). Accordingly, trust in IS field has been divided into initial and continuous trust to reflect the differences between the trust an individual develops before and after their initial interaction stage with the service (McKnight et al., 1998; Siau and Shen, 2003; Kim, 2012; Gao et al., 2017). Initial trust reflects the stage in which trustor (the potential adopter) lacks credible and meaningful information about the trusted party's behavior (the online service provider or online service) (McKnight et al., 2004). In such a stage, trust usually develops through quick inferences and assumptions (Meyerson et al., 1996) based on available secondhand information and first impression cues (McKnight et al., 2002). On the other hand, continuous trust reflects the stage at which the trustor has become familiar with trustee behavior; such trust develops on the basis of the information obtained from previous interactions with the service (Kim, 2012; Guo et al., 2016).

Yet, the term “initial trust” in information systems research has been interpreted in different ways with researchers distinguishing between pre-initial interaction and initial interaction trust stages (Komiak and Benbasat, 2004; McKnight et al., 2004). Although in both stages the trustee has not yet engaged in a direct relationship with the trusted party, the differences between the two stages are still significant in terms of trustor familiarity with trustee behavior. According to McKnight et al. (2004), the pre-initial interaction stage ends when the potential adopter decides to explore the new online service for the first time. In such stage, potential adopters become initial users and start to assess service provider and its online service trustworthiness based on first-hand, credible information, acquired by experiential factors, such as system quality, perceived ease of use and navigation, and information quality. Thereby creating a stage characterized by partial familiarity as opposite to the pre-initial interaction stage in which potential adopters are still unfamiliar with trustee behavior due to the absence of direct experience with the service. Hence, the factors forming potential adopters’ trust in the pre-initial interaction stage may significantly differ from those in the initial interaction stage.

The differences between the two stages become even more critical in mobile environments, such as mHealth. This is because the initial-interaction stage in which the navigation and exploration of the service takes its place requires the download and installation of mHealth app on potential adopters' smartphone or tablet. Unless potential adopters form positive trust expectations toward mHealth service providers and their mHealth services during the pre-initial interaction phase, they will probably not be willing to download and install mHealth services on their mobile devices. Earlier researchers have emphasized the importance of inducing pre-initial trust in the acceptance and use behavior of new technologies as it can set the tone for future relationships and interactions (McKnight et al., 1998; Goa et al., 2017). Consequently, a deeper investigation of the factors contributing to the development of potential adopter's trust in mHealth services and trust in mHealth service providers at the pre-initial interaction stage is vital to understand mHealth acceptance behavior from a trust perspective.

3.2.3 Factors Affecting Trust in mHealth Acceptance Research

While the effect of trust on mHealth acceptance behavior has been recognized by earlier research, less attention has been devoted to the factors underlying its development at the pre-initial interaction stage. Among the limited studies investigating trust at the pre-initial interaction stage, Deng et al. (2018) have built their work on the notions of TAM and perceived risk theory to identify the factors influencing potential adopters' trust in mHealth service providers from a technological perspective. The findings showed a strong negative correlation between legal concerns, privacy, performance risks, and trust in mHealth service providers, while no effect was found between perceived ease of use, perceived usefulness, and potential adopters' trust in mHealth service providers at the pre-initial interaction stage. On the other hand, the study of Meng et al. (2018) has explored the process by which potential adopters' trust was transferred from offline healthcare channels (hospital visits) to online healthcare channels (mHealth services) through the lens of Trust Transfer Model (TTM). The central concept underpinning TTM is that trust can be transferred cognitively between similar entities by transferring the attributes of the known entity to the unfamiliar one (Stewart, 2003). Accordingly, the findings suggested that trust in mHealth services is largely driven by one's trust in the service providers' offline healthcare services, moderated by personal factors (declining health conditions) and institutional factors (hospital support). Yet, this may not be the case for all mHealth service providers in which the mobile service provider is already known to the potential adopter based on previous offline interactions. Some mHealth services are pure online services in which the service, service provider, and healthcare/business process are all digitalized (Turban et al., 2002). Hence, it is evident from earlier findings that the factors promoting potential adopters' trust in mHealth service providers, and their mobile services are still an open question in the current mHealth acceptance literature.

Drawing on previous studies on online trust in the pre-initial interaction literature, evidence suggests that trust can be cognitively driven by various factors. These factors can be broadly categorized into social, technological, personal, institutional, and behavioral dimensions. Table 3.2 reviews the studies that have examined the factors contributing to the development of potential adopters' online trust in the pre-initial interaction stage, the theory/s used in the investigation, the entity of trust (e.g., online services and/or their service provider), and the country and context in which the study was conducted. While the promoters of individuals trust in mHealth service provider and its mHealth services has been investigated from technological, institutional, and personal perspectives, less attention has been given to the effect of factors from social and behavioral dimensions. Earlier evidence in innovation diffusion and IS acceptance research suggests that an individual's beliefs can be profoundly influenced by social forces, such as social influence (Rogers 2014; Venkatesh et al. 2000; Bhattacherjee, 2000). Although the effect of social influence on trust has been recognized in the studies of Li et al. (2008), Alsajjan and Dennis (2010), and Chaouali et al. (2016), it has been extensively investigated from the perspective of traditional IS theories specifically, TRA and its developments UTAUT, TAM, and TBP. These theories assume that social influence primarily operates from a normative perspective (Venkatesh et al. 2003; Davies et al., 1998; Ajzen et al., 1991). However, research in social psychology has long recognized the difference between normative and informative social influence in human social environments. According to Deutsch and Gerard (1955), social influence does not solely consist of group norms (normative social influence) but also consists of information delivery (informational social influence). Using only normative influence may not capture the full extent of social influence (Kim and Park, 2011; Li, 2013). Therefore, a more robust view of both informational and normative social influence is required (Li, 2013; Green, 1998) to gain deeper understanding of the factors promoting potential adopters trust in mHealth acceptance context.

In addition to being socially promoted, trust might also be fostered by behavioral factors, such as facilitating conditions. Facilitating conditions are generally viewed as situational factors that can make an act easy to do (Lu, Yu, and Liu, 2005). These facilitating conditions are specifically designed to reduce technology use barriers and to increase individuals' control over the preformed behavior (Venkatesh et al. 2003; Ajzen et al., 1991). In the absence of direct knowledge with mHealth services, facilitating conditions can build potential adopters trust by adding a level of assurance over the expected outcomes from one's interaction with mHealth services. In other words, facilitating conditions may serve as a trust building mechanism in the early stages of mHealth acceptance behavior as it may convey to potential adopters that beneficial behaviors are likely to occur because favorable contextual conditions are in place that are beneficial to the outcome success. Accordingly, further research is needed to understand the role facilitating conditions play in trust in mHealth acceptance research.

While the importance of technological factors as antecedents of trust has been recognized in mHealth acceptance research, less attention has been given to the innovation attributes from innovation diffusion theory. Innovation diffusion theory has long been recognized for its ability in explaining the forces underlying individuals' initial acceptance of innovative technologies. It proposes a set of innovation attributes which is believed to act as motivators to influence people's innovation acceptance/rejection decisions, known as relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2013). Although it is commonly believed by many online trust researchers that the concept of initial acceptance in IS theories aligns with the central concept of initial trust (Liu et al., 2006; Aljaafreh et al., 2014; Deng et al., 2018; Guo et al., 2017), less attention has been given to innovation attributes from IDT compared to the abundant research on other IS theories such as TAM and UTAUT, which assumes that perceived ease of use and perceived usefulness are the main characteristics of an innovation that can affect one's trust in the technology or its service provider. Given that mHealth is an emerging mobile service, potential users are more likely to perceive mHealth as an innovative service in which mHealth attribute may come into play; especially, as trust in pre-initial interaction stage is primarily promoted by available second-hand information and first impression cues (Mcknight et al., 2004).

Table 2.3 Literature on Trust in the Pre-Initial Interaction Stage

Study	Country/ Sample	Trust Antecedence					Trustor/Trustee	Theory	Dependent Variables	Context
		Institutional	Social	Technological	Behavioral	Personal				
1. Li et al. (2008)	USA (399)	Organizational Situational Normality, Organizational Structural Assurance, Cognitive Reputation, Technological. Situational Normality, and Technological Structural Assurance	Subjective Norms	x	x	Personality Faith in Humanity, Personality Trusting Stance, and Cost/Benefit Calculation	Consumer trust in technology	Theory of Reasoned Action	Trusting Believes, Trusting Attitude, and Trusting Intention	eGovernment
2. Kim et al. (2009)	South Korea (192)	Firm Reputation and Structural Assurance in Mobile Banking	x	Relative Benefits of Mobile Banking	x	Personal Propensity to Trust	Consumer trust in technology	x	Initial Trust in Mobile Banking and Use Intention of	mBanking

									Mobile Banking	
3. Chandra et al. (2010)	Singapore (109)	Perceived Reputation, Perceived Structural Assurance, and Perceived Opportunism	x	Perceived Environmental Risk	x	x	Consumer trust in technology	TAM	Consumer trust in M-Payment System, Perceived Ease of Use, Perceived Usefulness, and Adoption Intention of M-Payment Systems	mPayment
4. Alsajjan and Dennis (2010)	United Kingdom (232) and Saudi Arabia (386)	x	Subjective Norms	Perceived Manageability	x	x	Consumer trust in technology	Integration of TAM and TBP	Perceived usefulness, Trust, and Attitudinal Intentions.	eBanking
5. Xin et al. (2015)	New Zealand (302)	Perceived Reputation of mobile service provider, Perceived	x	Perceived Environmental Risk	x	Uncertainty Avoidance and Disposition to Trust	Consumer trust in technology	x	Trust and Intention to Use Mobile Payment	mPayment

			reputation of Mobile payment Vendor, perceived opportunism of Mobile Service provider, and Perceived Structural Assurance								
6.	Chaouali et al. (2016)	Tunisia (245)	x	Social Influence	x	x	Counter-Conformity Motivation	Consumer trust in Physical Bank and Technology	U TAUT	Trust in physical bank, Trust in Internet banking, Performance expectancy, expectancy, and Intention to adopt Internet banking	eBanking
7.	Meng et al. (2019)	China (395)	Hospital Support	x	x	x	Declining Health Conditions	Consumer trust in technology	Trust Transfer Theory	Trust in mHealth Services and Intention to	mHealth

									Use mHealth Services	
8. Deng et al. (2018)	China (388)	x	x	Perceived Ease of Use, Perceived Usefulness, Privacy Risk, Legal Concern, and Performance Risk	x	x	Consumer trust in Service Provider	TAM	Trust and Adoption Intention	mHealth

2.3 Anxiety in mHealth Acceptance Research

Anxiety is a negative emotional state accompanied by feelings of discomfort, fear, unease, apprehension, tension, and worry (Freud, 1936; Beckers et al., 2007). It arises in situations characterized by uncertainty in the presence of an unpredictable threatening event with possible negative consequences (Lazarus 1991). As an emotional state, anxiety is largely tied with the personal interpretations (appraisals) one makes about the occurrence of the threatening event itself and its possible consequences (Frijda 1986; Roseman 1984). Similarly, Bandura (1997) describes anxiety as "a state of anticipatory apprehension over possible deleterious happenings" (p. 137).

In the acceptance behavior of new technologies research, anxiety has received research interests as it can inhabit individuals' technology adoption actions or cause changes to their action readiness (Beaudry and Pinsonneault, 2010; Venkatesh, 2000; Meuter et al., 2003). Earlier IS researchers believes that in the acceptance process of new technologies, individuals anxiety can be elicited by different IS use events/situations (Beaudry and Pinsonneault, 2010). Such anxiety is used to reflect the temporary emotional distress an individual experiencing in response to a particular external stimulus perceived as important and relevant to an individual in a situation characterized by ambiguity and uncertainty (Beaudry and Pinsonneault, 2010; Celik, 2016).

A closer look at mHealth acceptance research shows that anxiety in earlier studies has been primarily investigated from the perspective of the anxiety individuals develop as emotional reaction to the use of mHealth service as a technological tool in general, known as technology anxiety, as shown in the studies of Houqe et al. (2017), Guo et al. (2013), Deng et al. (2014), and Rajak et al. (2021). Such type of anxiety, according to Troisi et al. (2022) and Meuter et al. (2003), is mainly concerned with understanding the anxiety individuals develop toward the use of technological tools in general from three different dimensions, namely: 1) the subjective dimension (one's ability to use technological tools); 2) the objective dimension (lack of technological skills and technology literacy); and 3) the behavioral dimension (one's state of mind regarding their ability and willingness to use technology related tools in general). Yet, the sensitivity nature of personal and health data in mHealth context may trigger individual's mHealth use anxiety as a specific emotional reaction to mHealth context. Such anxiety is elicited by the fears of losing control of one's information confidentiality when using mHealth services;

especially, in the light of the increased reports about privacy violations in the healthcare industry. For example, recent reports show that over 88% of available mHealth apps in the market had included a code that shared users collected data with unauthorized third parties, and that 23 % of these data transmissions has taken place on insecure communication protocols (Tangari et al., 2021). Such healthcare service provider practices may lead potential adopters to resist the use of mHealth services despite their observed advantages due to the anxiety associated with their use consequences, especially before their initial interaction stage with the service.

Furthermore, while the importance of anxiety has been acknowledged in mHealth acceptance research in general, less attention has been given to the factors affecting it particularly before the initial interaction stage with the service. Research and theory have long held the view that anxiety as emotional state is dynamic in that it can be affected by personal and environmental factors (Thatcher and Perrew, 2002; Marakas et al., 2000). However, less is understood about the factors affecting individuals' anxiety when accepting mHealth services for this first time. As an emotional factor that is closely related to individuals' mHealth use intentions, it is therefore crucial for mHealth service providers to gain further insights into the factors affecting potential adopters' anxiety to mitigate it in its early stages.

2.4 Theories and Concepts Underlying the Development of the Proposed Research Model

2.4.1 Innovation Diffusion Theory

The Innovation Diffusion Theory (IDT) is one of the most widely used theories in predicting individuals' acceptance of new technologies due to its ability to explain why innovative technologies like mHealth services diffuses within a social system (Agarwal and Prasad, 1998; Al-Jabri et al., 2012). IDT describes an 'innovation' as an idea, object, or practice that is perceived as new by its potential adopters (Rogers, 1995). The theory further describes 'diffusion' as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (Rogers, 1995, p. 5). The theory assumes that the diffusion of new innovations is a function of four elements: the innovation itself, communication channels, time, and social system. Among these elements, Rogers emphasizes the importance of innovation attributes in an individual's adoption of new technologies (Rogers, 2003). According to IDT, the adoption of an innovation does not happen simultaneously within a social system rather it evolves over time and depends primarily on the acceptance/rejection decisions of the members of a social system (Rogers, 2014). These acceptance/rejection decisions are to a great extent determined by five innovation attributes, relative advantage, compatibility, complexity, trialability, and observability, as shown in Table 2.3. To expand the use of these innovation attributes to IS acceptance and use area, Moore and Benbasat (1991) have extended the original set of the attributes identified by IDT to seven attributes since some of these attributes have been found to tap into different theoretical concepts, as shown in Table 2.3.

Table 2.3 Innovation Attributes in IS Research

Attribute	**Definition**	**Originality**
Relative Advantage	The degree to which an innovation is perceived as better than the idea it supersedes.	Relative Advantage
Image	The extent to which the use of an innovation is perceived as enhancing one's image or status.	Relative Advantage
Ease of use	The extent to which a person believes that the use of the innovation will be free of efforts.	Complexity
Trialability	The degree to which an innovation can be experimented with on a limited basis.	Trialability
Compatibility	The degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of its adopters.	Compatibility
Visibility	The degree to which the use of the innovation is apparent to the adopter in their social surroundings.	Observability
Results Dimensionality	The extent to which the results of the innovation can be observed and communicated with others.	Observability
Voluntariness	The extent to which individuals has the freedom to use or not to use the innovation.	New Construct
Adopted from Moore and Benbasat (1991)		

In an attempt to understand potential adopters' acceptance of mHealth services from a trust-anxiety perspective, this research therefore draws on the innovation attributes identified by IDT and IS research as the predictors of an individual's trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety from a technological aspect. This is because in the absence of first-hand experience with mHealth technology, individuals' internal beliefs and affective reactions are more likely to be affected by available information around them. It is believed by many IS acceptance and use researchers that in the early stages of the adoption process of new technologies, innovation attributes usually act as environmental informational cues (Bhattacherjee, 2000; Nikhashemi et al., 2021). Such environmental informational cues can serve as a source of information about mHealth service's performance and its service provider's behavior. Accordingly, these technological attributes therefore may serve as the foundation based on which potential adopters trust and anxiety responses are formed around mHealth technology before their initial interaction stage with the service.

Yet, since the predictive power of these innovation attributes significantly differs across contexts and the scope in which they are investigated (Mun et al., 2006; Agarwal and Prasad, 1997), this research therefore has excluded image, compatibility, result demonstrability, and voluntariness from the proposed research model as they are less relevant to either the research scope or its context. For example, this research has excluded compatibility and result demonstrability since such factors can be only assessed when the adopter has initially experienced mHealth system for the first time, even if no initial transaction has been placed, especially as these two factors are highly subjective and depend primarily on potential adopter's experiential evaluations and judgments. On the other hand, given that image is more of a socio-personal factor than a socio-technological factor like visibility, such a factor therefore cannot be controlled by service providers when promoting their mHealth services to their intended users, and thus it has been excluded from the proposed research model. In addition, this research has excluded voluntariness from the proposed research model since mHealth services are voluntarily used.

While innovation attributes have been recognized for their effectiveness in predicting individuals' acceptance of new technologies, they only examine the factors affecting individuals' acceptance of mHealth services from a technological point of view. However, given that individuals' cognitive beliefs before the initial interaction stage with the service are largely shaped by first impression cues and second-hand information (McKnight et al., 2002), simply focusing on technological factors to predict individuals' internal perceptions of mHealth service provider and its mHealth technological attributes may not be sufficient to explain individuals' acceptance behavior of mHealth services from a trust perspective. Therefore, apart from innovation attributes, this study utilizes interpersonal social influence and external social influence from social influence literature and facilitating conditions from social psychology and IS research as social and behavioral predictors of individuals trust in mHealth acceptance research.

2.4.2 Social Influence

According to social psychology and behavioral research, one of the key factors affecting an individual internal beliefs is social influence (Deutsch and Gerard, 1955; Kaleman, 1958). It is generally used to reflect the perceived social pressure on an individual to perform a given behavior (Venkatesh and Brown, 2001). Such pressure is exerted through messages and signals to help individuals in shaping their beliefs and perceptions formed around a given product/service or an activity when preforming a behavior for the first time (Salancik and Pfeffer, 1978; Fulk and Boyd, 1991; Fulk et al., 1990; Song et al., 2014). Given the critical role social influence can play in the formation process of individuals' internal beliefs, this research has therefore considered social influence as one category of environmental stimuli affecting potential adopters' trust in mHealth service and its mHealth service provider from a social dimension.

In social psychology, Deutsch and Gerard (1955) have differentiated between two types of social influence in an individual social environment: normative and informative. Normative social influence occurs when individuals conform with the common expectations held by the members of their referent group by changing their beliefs to adopt a similar behavior, while informative social influence occurs when an individual accept information gained from another as evidence about reality and consequently internalize it into one own belief system when preforming the induced behavior (Deutsch and Gerard, 1955; Bhattacherjee, 2000). The concept of normative and informative social influence is in line with the concept of communication channels in IDT. Many researchers in IS and innovation diffusion area have identified non-interpersonal verbal communication channels, such as mass media (e.g., media reports and advisement), as one form of social influence in an individual social environment known as external influence (Venkatesh and Brown, 2001; Rogers 2014; Bhattacherjee, 2000; Song et al., 2014). External influence is used to reflect the extent to which information provided via mass media reports, expert opinions, and other nonpersonal informational sources, influence potential adopters' use of a new technology, which has been classified as an informative social influence (Bhattacherjee, 2000). In addition to external influence, individual's perception can be also influenced by messages and signals exerted through interpersonal verbale communication channels, such as those from friends, family, colleagues, and other prior adopters known to the potential adopters (Bhattacherjee, 2000). Such social influence in IS and innovation diffusion research is usually referred to as interpersonal influence, which has been classified as a normative social influence (Bhattacherjee, 2000). Accordingly, this study utilizes external and interpersonal social influence as two factors influencing potential adopters trust in mHealth service and mHealth service provider from a social aspect.

2.4.3 Facilitating Conditions

Another theoretical concept underpinning the development of the proposed research model is facilitating conditions. The concept of facilitating conditions was first coined by Triandies (1977) in the theory of interpersonal behavior, in which it was defined as "objective factors out there in the environment that several judges or observers can agree make an act easy to do" (p. 205). By extending it to the IS field, facilitating conditions have been conceptualized and operationalized in different ways, with researchers differentiating between resource and technological facilitating conditions (Venkatesh et al., 2001; Tylor and Todd, 1995). Resource facilitating conditions are generally used to reflect the technological support and opportunities available for each individual, which are necessary for performing the behavior. At many online service consumption settings at the customer level, resource facilitating conditions are largely tied to customers environment and include factors such as money, time, internet availability, mobile devices, and technology use skills and knowledge. On the other hand, technological facilitating conditions are largely tied to the technology environment of the service provider itself and include factors such as technology use instructions, online tutorials, and technical support centers. Such facilitating conditions are specifically designed to remove the barriers associated with the use of the new technology (Venkatesh et al., 2000; Taylor and Todd, 1995). Given that resource facilitating conditions are less likely to be managed by service providers when promoting their mHealth services, this research therefore excludes resource facilitating conditions from the scope of the proposed research model and focuses more on the external facilitating conditions related to the technology environment. Accordingly, this research utilizes facilitating conditions as an environmental stimuli affecting potential adopters trust in mHealth service provider from a behavioral aspect.

2.4.4 Stimuli-Organism-Response

Stimuli-Organism-Response (SOR) is an environmental psychological theory built on the basis of stimuli-response model (Mehrabian and Russell, 1974). It views an individual's behavior as a behavioral reaction that steams from the core cognitive and emotional responses affected by environmental stimuli (Mehrabian and Russell, 1974; Bitner, 1992; Jacoby, 2002). These environmental stimuli can be found in various aspects of the environment surrounding an individual in the behavioral context. For example, they can be found in the form of technological factors (e.g., perceived ease of use, performance expectancy, perceived quality, trialability, and relative advantages), social factors (e.g., advertisement, government/social support, laws and regulations, interpersonal social influence, and media influence), institutional factors (e.g., reputation, return policy, and privacy policy), situational factors (e.g., health statutes, money in hand, promotions, and service availability), and behavioral factors (e.g., facilitating conditions, perceived behavioral control). On the other hand, organisms are used to reflect the cognitive and emotional responses intervening between a person's final reaction and an environmental stimulus (Jacoby, 2002). Response, on the other hand, is defined as a non-variable behavioral reaction that streams from an individual's cognition and emotional responses (Mehrabian and Russell, 1974).

In mHealth research, SOR has been utilized by a number of researchers to investigate individuals initial use behavior of mHealth services. For example, the study of Cao et al. (2020) has drawn on SOR model to understand how factors related to mHealth design (information overload and system feature overload) can lead to negative responses such as fatigue and technostress when using an mHealth service for the first time. It has also been utilized by the study of Lui, Lu, Li, and Zhao (2022) to investigate the relationship between mHealth content presentation (platform information presentation, guidance information presentation, and relational information presentation), internal experience (perceived value and trust), and mHealth adoption intentions (willingness to participate and willingness to recommend).

In addition to being effective in explaining individuals’ initial use behavior of innovative technologies, earlier IS researchers indicate that SOR is also effective in explaining potential adopters’ acceptance behavior of new technologies particularly in the pre-initial use stage (Lee et al., 2022; Watson et al., 2018; Nikhashemi et al., 2021; Wakefield et al., 2015). Accordingly, this study utilizes SOR theory as an overarching framework for structuring the proposed research model for two reasons. First, SOR offers a structured theoretical lens for capturing the external stimuli, internal psychological responses, and behavioral reactions constituting an individual’s behavior. Second, the SOR paradigm offers a scope for incorporating both an individual’s cognitive and emotional states when performing a behavior for the first time. Accordingly, SOR has been used as an overarching framework for organizing the proposed research model since it can provide a holistic view of individuals mHealth acceptance behavior.

Specifically, the proposed research model posits that an individual’s mHealth use intention (behavioral reaction) is a function of three factors: trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety (internal cognitive and emotional responses). Trust in mHealth service and trust in mHealth service provider are utilized as two beliefs affecting individuals' mHealth acceptance behavior from a cognitive perspective, while mHealth use anxiety as a negative emotional state affecting mHealth acceptance behavior from an emotional perspective. Given that trust and anxiety are dynamic in their nature in that they can be affected by external factors surrounding an individual in the behavioral context, this research, therefore, draws on innovation attributes, external and interpersonal social influence, and facilitating conditions from innovation diffusion, social psychology, and IS research to provide a comprehensive understanding of the factors affecting individuals trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety from technological, social, and behavioral dimensions.

2.5 Summary of the Research Gaps

In an attempt to understand individuals mHealth acceptance behavior, many mHealth researchers have relied on traditional IS acceptance models, such as TAM, PMT, UTAUT, and MM, as the basis for their study, investigating whether these models' constructs are also likely to predict potential adopters mHealth use intention, while others have utilized the cognitive-affective attitude, privacy-personalization, and customer value literature to gain further insights into the factors affecting potential adopters mHealth use intention. While previous mHealth studies have shed light on the key factors affecting potential adopters mHealth acceptance decisions, many of these factors have been investigated from the positive emotional reactions, attitudes, and cognitive factors an individual forms around the technology itself or one's health. Yet, the sensitive nature of health services may make mHealth use intentions less associated with the factors identified by traditional IS acceptance models, which were originally developed to understand employees generic work-related technology acceptance behavior.

With the increased uncertainties surrounding mHealth use environment in terms of its performance and its service provider behavior, potential adopters' mHealth acceptance experience is more likely to be dominated by internal psychological factors, such as trust and anxiety. While the importance of trust, from a cognitive perspective, and anxiety, from a negative emotional perspective, in mHealth use intention has been recognized by earlier researchers in mHealth acceptance research, individuals mHealth acceptance behavior has been rarely explored from a trust and anxiety perspective in the existing literature.

Furthermore, a closer look at mHealth acceptance behavior from an anxiety perspective shows that previous research focus was primarily on the anxiety individuals develop in terms of their fears of being unable to use mHealth services as a technological tool, known as technology anxiety. However, as stated earlier, with the increased uncertainties surrounding mHealth service environment in terms of its service providers behavior, mHealth services may trigger individuals mHealth use anxiety as a reaction to their fears of losing control of their information confidentiality when using mHealth services. Such a type of anxiety is specifically related to mHealth acceptance context.

Besides this, the review of the literature shows that less consideration has been given to the factors affecting potential adopters' trust and anxiety in mHealth acceptance research. It is believed by many information systems researchers that trust and anxiety are dynamic factors in their nature in that they can be affected by environmental and personal factors surrounding an individual in the behavioral context. Therefore, further investigations are required to gain a comprehensive understanding of individuals mHealth acceptance behavior from a trust-anxiety perspective. Accordingly, in an attempt to understand potential adopters mHealth acceptance behavior from an anxiety and trust perspective, this research therefore proposes a theoretical model that examines mHealth acceptance behavior from three perspectives: trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety. The proposed model was built on the basis of SOR and research from innovation diffusion, social psychology, and IS field to provide a comprehensive understanding of mHealth acceptance behavior from a trust-anxiety perspective. In the next chapter, the proposed research model will be discussed in further detail to establish its hypotheses and draw its theoretical rationale.

Chapter 3: Research Model and Hypothesis Development

Following the extensive literature review from the previous chapter, this chapter further discusses the proposed research model and the hypotheses underlying its development. It starts by first introducing the proposed research model of this study by elaborating on its structure, the factors underlying its development, and the definition of these factors. It then describes the relationship between these factors to draw the proposed research model theoretical hypotheses and to explain the rationale behind its development.

3.1 The proposed Research Model

As shown in Figure 3.1, this study proposes a theoretical model that attempts to investigate potential adopters' mHealth acceptance behavior from a trust-anxiety perspective. The proposed research model builds its theoretical foundation on the Stimuli-Organism-Response framework (SOR) and depicts potential adopters' mHealth use intention as a function of three factors: mHealth use anxiety, trust in mHealth service, and trust in mHealth service provider. mHealth use anxiety is an emotional factor affecting mHealth use intention from an anxiety perspective, while trust in mHealth service provider and trust in mHealth service are two cognitive beliefs affecting mHealth use intention from a trust perspective.

The proposed model further depicts the factors affecting potential adopters' trust in mHealth service provider, trust in mHealth service, and mHealth use anxiety from three dimensions: technological, social, and behavioral dimensions. From a technological dimension, the proposed model incorporates trialability, relative advantage, ease of use, and visibility from innovation diffusion and IS research as a predictors of the factors affecting potential adopters' trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety. From a behavioral dimension, the proposed model incorporates facilitating conditions from psychology and IS research as a predictor of potential adopters' trust in mHealth service provider. On the other hand, the proposed model incorporates external social influence and interpersonal social influence from social psychology and IS research as predictors of trust in mHealth service provider, trust in mHealth service, and visibility. The definitions of these factors are presented in Table 3.1.

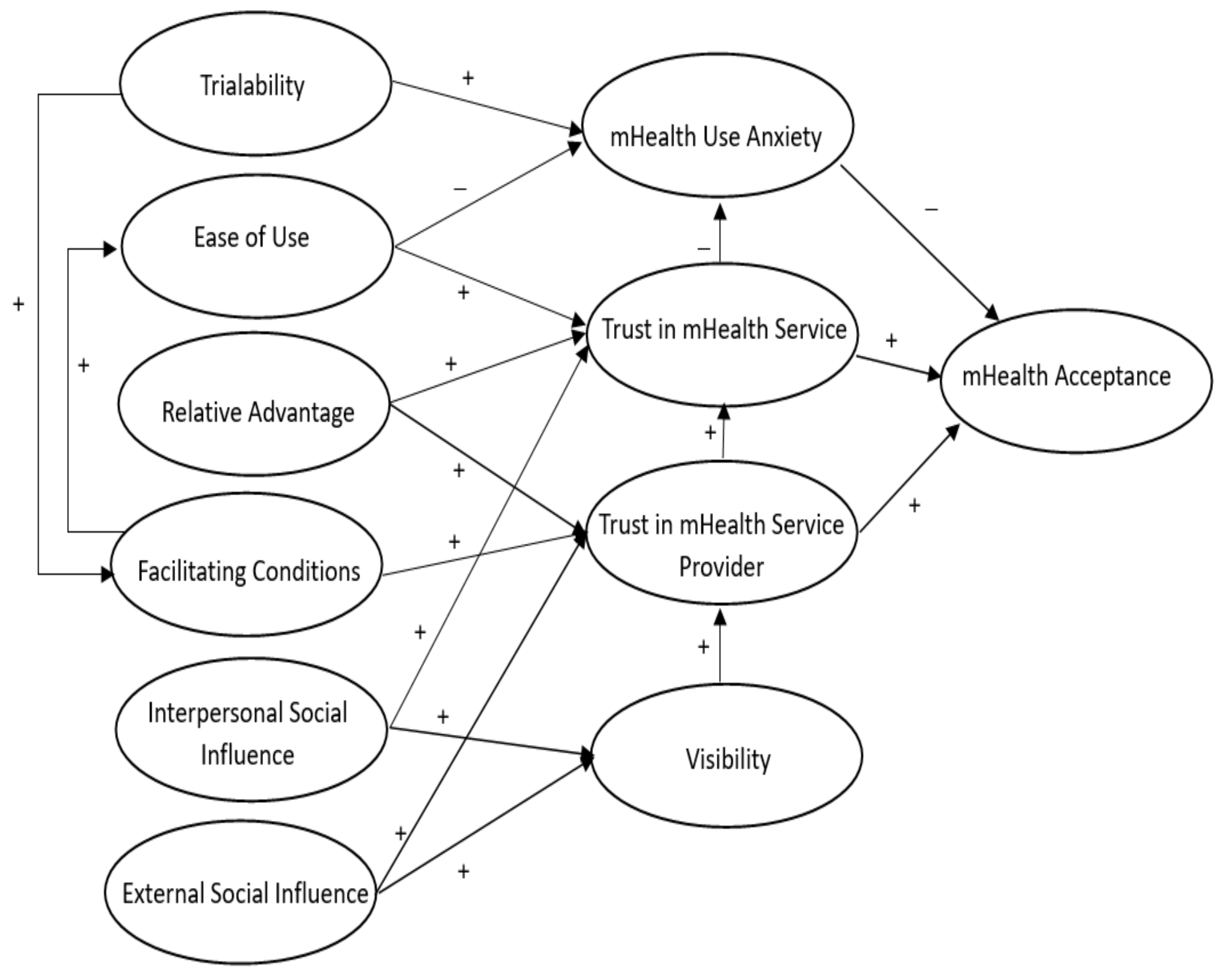

Figure 3.1 The Proposed Research Model

Table 3.1 Definition of Constructs

Construct	Definition
Relative Advantage	Relative advantage refers to the degree to which the use of mHealth services is perceived as superior to the idea of in person doctor visits (More and Benbasat, 1991).
Ease of Use	Ease of use is used to reflect the degree to which an individual believes that the use of mHealth service would not require a lot of efforts (Davis et al., 1998).
Trialability	Trialability is used to reflect the extent to which an individual wants mHealth services to be available for trial before being fully utilized (Tan and Teo, 2000; Al-Jabri and Sohail, 2012).
Facilitating Conditions	Facilitating conditions reflect the degree to which an individual believes that organizational and technological infrastructure exist to support the use of mHealth services (Venkatesh et al., 2003).
External Social Influence	External social influence is used to reflect the extent to which information from media and nonpersonal sources influence an individual to use mHealth services (Bhattacharjee, 2000; Roger, 1995; Song, 2016).
Interpersonal Social Influence	Interpersonal social influence is used to reflect the extent to which members from one’s social network (e.g., friends, family, and other adopters known to the potential adopter) influence him/her to use mHealth services (Bhattacharjee, 2000; Song, 2016).
Trust in mHealth Service Provider	Trust in mHealth service provider is used to reflect the extent to which an individual believes in a service provider’s competence, benevolence, and integrity (Gefen et al., 2003).

Construct	Definition
Trust in mHealth Service	Trust in mHealth service is used to reflect the extent to which individuals believe in the functionality and reliability of mHealth service (Thatcher et al., 2013).
Visibility	Visibility is used to reflect the degree to the use of mHealth services is apparent to an individual in their social surroundings (More and Benbasat, 1991).
mHealth Use Anxiety	mHealth use anxiety is used to reflect the fear an individual experiences when faced with the possibility of losing one's information confidentiality when using mHealth services.
mHealth Acceptance	mHealth acceptance is defined as extent to which individuals intend to use mHealth services (Ajzen et al., 1990; Davis et al, 1998; Venkatesh et al., 2003).

3.2 Hypotheses Development

3.2.1 Hypotheses Related to Trust and Anxiety

3.2.1.1 mHealth Use Anxiety

In the absence of direct mHealth use experience, individuals may hesitate to use mHealth services due to the increased anxiety associated with their information confidentiality. In this research, mHealth use anxiety is used to reflect the fear an individual experiencing when faced with the possibility of losing one's information confidentiality when using mHealth services.

As a personalized service, mHealth functionality relies heavily on the data users release to service providers over mobile networks, in which information confidentiality arises as an issue when accepting mHealth services (Guo et al., 2016; Schnallet et al., 2015). In mHealth context, information confidentiality issues are largely triggered by the way mHealth service providers manage their online customers' disclosed information over mobile networks. Research in privacy and security literature suggests several dimensions related to organizations' information privacy practices that can be linked with potential adopters information confidentiality issues in mHealth context, such as: 1) collecting and storing users' identifiable information; 2) ineffectively managing the corrected errors in users' previously collected data; 3) allowing unauthorized secondary use of users' information by external/internal parties; and 4) permitting improper access to users' information by unauthorized users (Smith et al., 1996). Such service providers online privacy practices can evoke potential adopters' mHealth use anxiety, particularly before their initial interaction stage with a mHealth service.

Anxiety has been frequently cited in IS adoption literature as one of the key factors inhibiting individuals' acceptance and use behavior of new technologies (Brosnan, 1998; Thatcher and Perrewé, 2002; Venkatesh et al., 2003; Beaudry and Pinsonneault, 2010). Research in psychology explains the relationship between mHealth use anxiety and mHealth use intention by showing how people cope with anxiety. Lazarus and Folkman (1984) suggest that people usually cope with anxiety by physically avoiding the stressor. Given that people tend to avoid situations that increase their anxiety (Compeau et al., 1999), this research therefore hypothesizes the following:

H1: mHealth use anxiety will negatively affect mHealth acceptance.

3.2.1.2 Trust in mHealth Service and Trust in mHealth Service Provider

Just like with other online services, the acceptance of mHealth services requires individuals to deal first with the increased uncertainties surrounding mHealth use environment in terms of mHealth performance and its service provider behaviour by taking psychological cognitive steps to reduce them. Trust, as a subjective cognitive belief reflecting individuals' expectations of the trusted party's attributes, has long been considered a key factor in alleviating the risks and uncertainties accompanying the acceptance experience of new technologies (Zhou, 2011; Gao et al., 2017; McKnight et al., 2002).

As the main entity through which healthcare services are delivered and consumed, trust in mHealth service becomes an important part of the intention individuals form toward the use of mHealth technology (Meng et al., 2019). Trust in mHealth service is used to reflect the extent to which an individual believes in the functionality and reliability of mHealth technology (Thatcher et al., 2013). Several researchers have shown a direct relationship between one's trust in a technology and their willingness to conduct transactions through mobile terminals (Kim et al., 2009; Zhou 2011; Zhou 2014; Chandra et al., 2010; Xin et al., 2015). Compared to offline forms of healthcare transactions, transactions conducted through mHealth channels are more vulnerable to service failures that may result in incomplete transactions. This is because the performance of mHealth services primarily depends on the processing capability and network connectivity of the smartphones and tablets used in using these services (Yang et al., 2014). Furthermore, the innovativeness of mHealth service as a virtual healthcare channel may increase individuals' doubts about the way in which traditional healthcare processes will be supported via mobile terminals. Accordingly, potential adopters need to build their trust in mHealth services to overcome the risks and concerns surrounding mHealth use environment in terms of its functionality and reliability. Pavlou (2003) indicates that trust is fundamental whenever risks, concerns, and uncertainties exist in online environments, as it can enhances the expectations of successful transactions. Similarly, previous research in mHealth acceptance context has shown that mHealth use intention is largely influenced by the level of an individual trust in mHealth service (Meng et al., 2019). Thus, this research hypothesizes the following:

H2: Trust in mHealth service will positively influence mHealth acceptance.

Trust in mHealth service may also play a role in lessening early stages mHealth use anxiety. As an emotional reaction, mHealth use anxiety is largely tied to the fears individuals develop around the confidentiality of their disclosed personal and health information over mHealth terminals. Such anxiety becomes even higher in mobile environments in which services are extremely personalized with tiny screens, simple features, and inconvenient inputs (Hwang et al., 2007). In such environments, potential adopters may feel that they are more likely to make mistakes (e.g., pressing the wrong keys, making the wrong transaction, entering the wrong data) when using mHealth services especially as they are still unfamiliar with its features. In such environments, trust can emerge as a fear reduction mechanism by increasing individuals' confidence in the performance of the used technology (Thatcher et al., 2007). When potential adopters believe that mHealth will have the necessary attributes to support their use of the system, they are more likely to feel that mHealth services will pose less risk to their disclosed information. Accordingly, this research hypothesizes the following:

H3: Trust in mHealth service will negatively influence mHealth use anxiety.

Trust in mHealth service provider is defined as the extent to which an individual believes in a service provider's competence, benevolence, and integrity (Gefen et al., 2003). It used to reflect the extent to which an individual believes that mHealth service provider will behave in a socially accepted manner to meet its obligations according to potential adopters' best interests (McKnight et al., 2004; Gefen et al., 2003). According to Reichheld and Schefter (2000), trust is an important precursor of one willingness to participate in offline transactions, in general, and in an online transactions, in particular, because of the ease at with which online providers can behave in an opportunistic manner. The mediated nature of mHealth service makes trust in mHealth service provider a central aspect of mHealth use intention. Unlike traditional means of healthcare processes (e.g., offline doctor visits), mHealth healthcare processes are notably characterized by (a) the extensive use of mobile communication technology with an open information transmission infrastructure, (b) the impersonal nature of online environment, (c) the ease by which information can be collected, processed (data mining), manipulated, and shared with other parties. Such environments, therefore, makes potential adopters vulnerable to service providers opportunistic behaviours, such as collecting and selling consumer data, misrepresenting service provider true qualifications, violating purchasing polices (Gefen et al., 2003). As an expectational belief, trust helps potential adopters reduce their social uncertainties about mHealth service providers behaviour by allowing them to subjectively rule out undesirable yet possible behaviours (Gefen et al., 2003). As mHealth service provider become more trusted, potential adopters are more likely more likely to develop positive intentions toward the use of mHealth service (Guo et al., 2016; Fox et al., 2018; Deng et al., 2018). Therefore, this research hypothesizes the following:

H4: Trust in mHealth service provider will positively influence mHealth acceptance.

Furthermore, trust in mHealth service provider may contribute to the development of trust in mHealth service. Previous research in the electronic commerce setting suggests that an individual's trust in one entity can be affected by its trust in another when accepting new technologies. For example, Thatcher et al. (2013) have found that trust in technology has contributed to the development of an individual trust in online service provider. However, unlike in an electronic service environment, individuals in a mobile service environment lack the ability to directly interact with mHealth services before configuring the application on their mobile devices. Therefore, this research hypothesizes the following:

H5: Trust in mHealth service will positively influence trust in mHealth service provider.

3.2.2 Hypotheses Development Related to The Factors Affecting Potential Adopters Trust and Anxiety

3.2.2.1 Trialability

In this research, trialability is used to reflect the extent to which an individual wants mHealth services to be available for trial before being fully utilized (Tan and Teo, 2000; Al-Jabri and Sohail, 2012). In the absence of direct experience, individuals feel most attracted to new technologies that offer them free personal trials of their main services and functions (Tan and Teo, 2000; Al-Jabri and Sohail, 2012; Rogers, 2014). This is mainly the case with mHealth services in which the innovativeness of mHealth services as a health technology may lead individuals to prefer the use of mHealth services on a personal trial basis before making a full commitment to the technology. From a potential mHealth adopter's perspective, personal trials allow them to assess the extent to which mHealth services can align with one's needs and circumstances. Accordingly, this research assumes that higher levels of trialability can lead to higher levels of facilitating conditions as trialability can be seen as a facilitating condition that can ease the use of mHealth services before the initial interaction stage with mHealth services. Accordingly, this study hypothesizes the following:

H6: Trialability will positively affect facilitating conditions.

Yet, simply bringing consumers to the point of trying an innovative personalized service, such as mHealth, is a challenging process (Meuter et al., 2005; Wood et al., 2006). This is because personal trials of mHealth services may require the disclosure of one's personal information (e.g., health and location data) in order for mHealth to operate. However, with the increased privacy concerns surrounding mHealth use environments, potential adopters may regard personal trials as a risky action as they could possibly become vulnerable to service providers' potential opportunistic behaviors, such as collecting and selling customers personal information to third parties (Hwang et al., 2007). Accordingly, this study assumes that trialability is more likely to foster potential adopters' mHealth use anxiety when accepting mHealth services and accordingly this research hypothesizes the following:

H7: Trialability will positively affect mHealth use anxiety.

3.2.2.2 Ease of Use

In line with Davis et al.'s (1998) definition, this thesis defines ease of use as the degree to which an individual believes that the use of mHealth service would not require a lot of efforts. Ease of use perception is largely tied to the assessment one makes about the effort involved in using a particular technology (Venkatesh et al., 2000). Such perception in the early stages of the acceptance process of new technologies is more likely to be stable across different domains of new technologies use experience (Venkatesh et al., 2000). In other words, in the absence of direct system experience, ease of use is more of a general belief reflecting one's expectations of the effort involved in using a new technology in general.

This research assumes that ease of use can play a critical role in mitigating early stages mHealth use anxiety. While the effect of ease of use on anxiety has not been explicitly verified in the existing IS acceptance literature, the relationship between the two can be explained through social cognitive theory. Social cognitive theory holds that one's perception of their ability to successfully execute a course of actions, known as self-efficacy, can work as a coping mechanism to overcome the negative emotional responses (e.g., anxiety) one encounters when performing a behavior for the first time (Bandura, 1977). Such perception, according to Bandura (1977), is more likely to stem from the general assessment one makes about his/her ability to perform the desired behavior which takes into account the effort needed in performing it. In the technology acceptance model, Davis et al. (1998) argues that in the early stages of the acceptance process of new technologies, ease of use perception is largely tied with the assessment an individual makes about his/her ability to use the new technology. Similarly, Venkatesh (2000) noted that in the absence of direct firsthand experience with the system, ease of use perception primarily stems from the confidence one has in their ability to use new systems in general. This is because in the early phases of the acceptance process of new a technology, people are unable to assess its usability, and therefore they tend to anchor their ease of use perception to their general beliefs about the experience of using new technologies and their ability to use new technologies in general (Venkatesh and Bala, 2008). This indicates that for first time mHealth adopters, mHealth ease of use belief mainly operate through their general perceptions about new mobile apps use experience and their ability to use such innovative apps.

Building on this logic, when potential adopters believe that it will be easy for them to configure and use mHealth apps on their smartphones/tablets, they are more likely to experience low levels of mHealth use anxiety. This is because, according to Keith et al (2015), when individuals believe that they are skilled in using new technologies, they tend to place greater trust in apps service providers and fewer risks in the app itself, even when the intentions of apps providers cannot be verified (Keith et al, 2015). Moreover, earlier evidence also suggests that an increase in ease of use perception is more likely to result in an increase in one's trust in the technology in terms of its functionality and reliability. For example, in the context of online banking, Alsajjan and Dennis (2010) have found a strong positive relationship between perceived manageability and trust in technology. Therefore, this study assumes the following:

H8: Ease of Use will negatively affect mHealth use anxiety.

H9: Ease of Use will positively affect users trust in mHealth service.

3.2.2.3 Relative Advantage

Relative advantage is another key innovation attribute in the diffusion and acceptance process of new technologies (Tornatzky and Klein, 1982; Rogers, 1995). It reflects an individual's perception of the benefits an innovation can offer over the idea it replaces (More and Benbasat, 1991). In line with Moore and Benbasat's (1991) definition, this study defines relative advantage as the degree to which an individual perceives mHealth services as superior to the idea of in person doctor visits. As an emerging service, mHealth provides its customers with a mobile channel to consume healthcare services. Unlike traditional offline healthcare channels, mHealth services can offer its potential adopters' observable benefits in terms of the increased convenience, control, and immediate access to healthcare services. Prior research in online trust literature suggests that such observed benefits may contribute to the formation of individuals' trust even before their initial interaction stage with the system (Koufaris & Hampton-Sosa, 2004; Kim et al., 2009). For example, in mobile banking context, Kim et al. (2009) have found a strong link between relative advantage and potential adopters' trust in mobile banking technology. Relative advantage has also been found to affect potential adopters' trust in online service providers in internet banking and mobile payment contexts (Susanto et al., 2013; Goa et al., 2017). This imply that relative advantage can boost potential adopters' trust in mHealth services and their service providers in the early stages of their acceptance process of mHealth services. This is due to the design of mHealth services, which aims to shift the power from service providers to patients to increase their control over disease management (Guo et al., 2016). Such design in return can provide mHealth potential adopters with practical evidence of service providers' caring behavior and their ability to provide mobile services that are functional and reliable to meet individuals' demands and satisfy their needs. Accordingly, this study assumes the following:

H10: Relative advantage will positively affect trust in mHealth service provider.

H11: Relative advantage will positively affect trust in mHealth service.

3.2.2.4 Visibility

In line with Moore and Benbasat (1991), this study defines visibility as the degree to which the use of mHealth services among the members of a social system is apparent to an individual in their social surroundings. As a technological attribute, visibility has long been seen as a key factor in the acceptance and use behavior of new technologies (Agarwal and Prasad, 1997) as it can affect the beliefs and attitudes a potential adopter forms around new technologies (Karahanna et al., 1999; Aloudat et al., 2014). According to Karahanna et al., (1999), in the absence of first-hand experience, visibility can provide observers with an effective source of evaluative information to learn more about new innovations.

This study assumes that in the early stages of mHealth acceptance behavior, visibility may boost potential adopters trust in mHealth service provider by forming individuals' favorable expectations about mHealth service provider behavior. Such a situation arises when potential adopters do not have complete information about mHealth service provider's true behavior and therefore they would infer its trustworthiness from the observation they make on others behavior in their social surroundings. Wang et al. (2013) indicate that information provided through others' behavior constitutes an integral part of the knowledge base on which individuals' perceptions of, and beliefs about an IS are formed. Prior research findings in electronic commerce support these arguments by showing that when the use of an online grocery website was apparent to a new customer, the new customer was more likely to find it as useful (Bonn et al., 2016). A similar situation has been seen in the context of mobile government location-based services in which heightened levels of usefulness perceptions were found to be strongly associated with heightened levels of visibility perceptions (Aloudat et al., 2014). Extending these assumptions to the pre-initial trust context, this suggests that when an mHealth service use becomes visible to a potential adopter in his/her social surroundings, the potential adopter is more likely to believe in the trustworthiness of mHealth service provider in terms of its competence, benevolence, and integrity. Accordingly, this research hypothesizes the following:

H12: Visibility will positively affect users' trust in mHealth service provider.

3.2.2.5 Facilitating Conditions

In line with Venkatesh et al. (2003), this study defines facilitating conditions as the degree to which an individual believes that organizational and technological infrastructure exist to support the use of mHealth services. In the early stages of the acceptance process of new technologies, Venkatesh et al. (2000) indicate that potential adopters will have a general perception of the available facilitating conditions to them based on their previous use experience with similar mobile services. As a general perception, facilitating conditions can provide potential adopters with a framework based on which they can rely to build favorable expectations about mHealth service provider behavior; specifically, in terms of its ability, integrity, and benevolence. This is because, according to Triandis (1980) and Venkatesh et al. (2000), facilitating conditions may convey a feeling of situational control. When people feel in control, they tend to build more confidence in the people they interact with. Facilitating conditions can build individuals trust in service providers by creating less uncertainty about its technology performance, which according to Ratnasingam et al. (2005) often reflects on one’s perceptions of service provider behavioral normality. Similarly, several researchers have confirmed the importance of facilitating conditions in building individuals trust perceptions in the contexts of wearable commerce (Gu, Wei, and Xu, 2015) and wireless mobile services (Lu et al., 2005). In addition to positively influencing individuals' trust in mHealth service providers, earlier evidence also suggests a strong link between ease of use perception and facilitating conditions in the early stages of the acceptance process of new technologies (Venkatesh et al., 2000). Therefore, this research hypothesizes the following:

H13: Facilitating conditions will positively affect trust in mHealth service provider.

H14: Facilitating conditions will positively affect ease of use.

3.2.2.6 Interpersonal and External Social Influence

Social influence has long been recognized as a key factor in the acceptance and use of new technologies. It reflects the perceived social pressure on an individual to perform a behavior (Venkatesh and Brown, 2001). From a social aspect, this study differentiates between two types of social influence in an individual's social environment: interpersonal and external social influence.

Interpersonal social influence is used to reflect the extent to which the members of one’s reference group (e.g., friends, family, and other adopters known to the potential adopter) influence him/her to use mHealth services (Bhattacharjee, 2000; Song, 2016). It emphasizes the social pressure exerted on an individual to comply with the referent group’s shared opinions and expectations. These opinions and expectations can generally define what an individual’s referent group considers as a normal behavior guided by the group’s shared values (Hong and Tam, 2006). In the absence of first-hand experiential data, potential adopters are more likely to be influenced by their reference group's opinions and expectations (Gefen et al., 2003). When a potential adopter feels that the people who they value their opinion approve and support the use of mHealth services and expect the members of their social group to do the same, they are more likely to build a favorable expectation toward mHealth services in terms of their functionality and reliability. In a similar vein, when a potential adopter feels that the people who they value their opinion disapprove their usage of mHealth services and expect them to do the same, potential adopters are more likely to build lower levels of trust toward mHealth services before their initial interaction stage with the technology. The relationship between interpersonal social influence and trust in mHealth services is largely based on the identification process (Bhattacharjee, 2000; Li et al., 2013). Identification occurs when potential adopters change their values and beliefs to comply with their shared group’s opinions and expectations (Kelman, 1958). Earlier IS research suggests that individuals are often motivated to comply with their reference group's opinions and expectations by the desire to maintain harmony and a favorable social image with their reference group (Kelman, 1958; Li et al., 2008; Venkatesh and Davis, 2001).

Prior research in the internet banking context has shown support for the positive relationship between interpersonal social influence and trust in mHealth services. For example, the study of Alsajjan et al. (2010) found that when potential adopters referent group thought that they should use internet banking, they were more likely to trust internet banking technology in terms of its functionality and reliability. A similar finding has been found in the study of Chaouali et al. (2016). Chaouali et al. (2016) found that interpersonal social influence had positively affected potential adopters trust in internet banking services even before their initial interaction stage with the service. Similarly, Li et al. (2008) indicated that in the adoption context of new technologies, interpersonal social influence positively affects potential adopters use intentions by boosting their trust in the new technology. Accordingly, this research hypothesizes the following:

H15: Interpersonal social influence will positively affect trust in mHealth services.

On the other hand, external social influence is used to reflect the extent to which information from media and nonpersonal sources influences an individual's use of mHealth services (Bhattacharjee, 2000; Roger, 1995; Song, 2016). Prior innovation diffusion research holds that information from media and nonpersonal sources can exert influences on potential adopters' opinions and expectations about an innovation even before their initial interaction with the innovation (Rogers, 1995). A view that is also supported by earlier IS acceptance research. Venkatesh and Brown (2001) identified external sources of information, such as media, as influential, especially at the early stages of the adoption process of new technologies. This study therefore assumes that when accepting mHealth services, external social influence may exert a positive influence on potential adopters' expectations of mHealth service provider behavior in terms of its competence, benevolence, and integrity. This is because external social influence can provide potential adopters with a means to learn more about service provider attributes as they offer rich, diverse, and non-redundant information about mHealth services (Grnovetter, 1973; Hansen, 1999).

Accordingly, this study assumes that when potential adopters feel that media reports and advertisements generally support the use of mHealth services, they are more likely to believe that mHealth service providers will behave in a socially acceptable manner to meet their obligations according to potential adopters best interests. On the other hand, when media reports are negatively formed around the use of mHealth services, potential adopters are less likely to trust mHealth service providers in terms of their competence, integrity, and benevolence when considering the acceptance of mHealth services for the first time. Earlier IS research suggests that the effect of external social influence on individuals' internal beliefs largely operates through the internalization process (Bhattacharjee, 2000; Song et al., 2013). Internalization occurs when an individual views information provided via media reports and advertisements as evidence of reality and consequently internalizes it into one’s own belief system when performing the induced behavior (Bhattacharjee, 2000). This means that information provided via media reports and advertisements may positively affect potential adopters mHealth use intentions by influencing their perceptions of mHealth service provider behavior. Accordingly, this research hypothesizes the following:

H16: External social influence will positively affect trust in mHealth service providers.

Furthermore, the central concept of innovation diffusion theory is the process by which an innovation is communicated through interpersonal and external communication channels over time among the members of a social system (Rogers, 1995). These communication channels do not only provide a means by which a message transfers from the communicator to the receiver, but they also help individuals in forming their perceptions about the visibility of such innovations among the members of their social system (Rogers, 2014). Before deciding whether to use mHealth services, individuals may observe the successful experiences acquired by their peers from their reference group (Lee, Cheung, Sia, and Lim, 2006). Such observations can increase the level to which an individual’s perceive the usability of mHealth services among their peers. Indeed, positive evaluations and visible use by outsiders are just as important as peer observation in shaping individual perceptions about the extent to which mHealth services are widely adopted and used by the members of their social systems. Therefore, this research assumes that external and interpersonal sources can positively influence potential adopters’ perceptions of mHealth's visibility.

H17: Interpersonal social influence will positively affect visibility.

H18: External social influence will positively affect visibility.

3.3 The Constructed Research Model Hypotheses

Following the literature discussion in section 2.4, this study develops a theoretical model that attempts to explain potential adopters mHealth acceptance behavior from a trust-anxiety perspective. The proposed research model, as shown in figure 3.1, depicts potential adopters mHealth use intention as function of trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety. It goes a step further by explaining the factors affecting potential adopters' trust and anxiety from technological, social, and behavioral dimensions. This section presents the 18 hypotheses underlying potential adopters' mHealth acceptance behavior from a trust-anxiety perspective. All of these hypotheses have been tested with empirical data from Saudi Arabia and United Kingdom, as will be discussed in further details in Chapter 5.

H1: mHealth use anxiety will negatively affect mHealth acceptance.

H2: Trust in mHealth service will positively influence mHealth acceptance.

H3: Trust in mHealth service will negatively influence mHealth use anxiety.

H4: Trust in mHealth service provider will positively influence mHealth acceptance.

H5: Trust in mHealth service provider will positively influence trust in mHealth service.

H6: Trialability will positively affect facilitating conditions.

H7: Trialability will positively affect mHealth use anxiety.

H8: Ease of Use will negatively affect mHealth use anxiety.

H9: Ease of Use will positively affect users trust in mHealth service.

H10: Relative advantage will positively affect trust in mHealth service provider.

H11: Relative advantage will positively affect trust in mHealth service.

H12: Visibility will positively affect users' trust in mHealth service provider.

H13: Facilitating conditions will positively affect trust in mHealth service provider.

H14: Facilitating conditions will positively affect perceived ease of use.

H15: Interpersonal social influence will positively affect trust in mHealth service.

H16: External social influence will positively affect trust in mHealth service provider.

H17: Interpersonal social influence will positively affect visibility.

H18: External social influence will positively affect visibility.

Chapter 4: Research Methodology

This chapter is concerned with the research methodology used to achieve the research aim and answer its research questions. It discusses in detail the research philosophy, research approach, data collection and analysis techniques used in this study. The chapter also discusses the measurement scale used to assess the proposed research model presented in Chapter3. It also discusses the pilot study and the sampling technique used for collecting research data. This chapter finally ends by discussing the research design used in this study.

4.1 Research Philosophy

The concept of research philosophy is commonly used in scientific research to describe the belief system underlying the development of knowledge (Saunders, Lewis, and Thornhill, 2003). This belief system is generally made up by a set of assumptions concerning the nature of reality and the reliability of knowledge claims made around the studied phenomenon. The philosophical assumptions that researchers hold about a given phenomenon (e.g., mHealth acceptance behavior) are to a great extent influenced by the way in which researchers view and perceive the world around them (Saunders, Lewis and Thornhill, 2003). These assumptions in turn can influence the process by which researchers collect and analyze the data formed around the studied phenomenon as well as the way in which these data are interpreted and explained (Crotty, 1998; Collis and Hussey, 2013; Myers et al., 2009). Given the importance of research philosophy in the methodological design of scientific research, the following sections will further discuss the underlying assumptions forming a research philosophy.

According to Guba and Lincoln (1994), any research philosophy is generally made up by three major assumptions, as following:

- Ontological Assumption. Ontology is a philosophical stance concerned with the nature of existence and structure of reality (Crotty, 1998). Its central question spins around “whether there is a social reality that exists independently from human conceptions and interpretations and whether there is a shared social reality or only multiple, context-specific ones." (Ormston et al., 2014, p.4). Objectivism and subjectivism are two different positions to ontology. Objectivism presumes that the real world in which social reality exists is made up of fixed objects that exist independently form its social actors (Saunders et al., 2003). On the other hand, subjectivism assumes that reality is socially constructed by the meaning attach to it by its social actors (Neuman, 2003).

- Epistemological Assumption. Epistemology, on the other hand, is "a branch of philosophy concerned with assumptions about knowledge, what constitute as acceptable, valid and legitimate knowledge, and how we can communicate that knowledge to others" (Saunders, Lewis and Thornhill, 2015, p. 716). This type of assumption is primarily concerned with the practices and procedures used in the development of knowledge claims when inquiring about reality. Therefore, epistemology is considered as one of the key assumptions in any research philosophy as it can affect the strategy (methodology) by which the development of knowledge is constructed (Grix, 2002).
- Methodological Assumption. This branch of assumption is generally concerned with describing the methods used in creating knowledge claims (Guba, 1990; Creswell 2003). The goal of this type of assumption is to justify and evaluate the reasons governing the selection and use of particular research methods and how the selected research methods link with the desired outcomes (Chua 1986; Wellington, 2000; Crotty, 2003).

These philosophical assumptions are the focal point based on which information systems paradigms are built on and outlined (Orlikowski and Baroudis, 1991; Guba, 1990). Generally, there are three main research paradigms underlying the development of knowledge in the information systems field, namely, positivism, interpretivism, and critical realism (Orlikowski and Baroudis, 1991). Each paradigm builds on a different set of world of views, assumptions, knowledge claim procedures and methods to provide researchers with a philosophical framework that guides their actions in the development of knowledge (Matthews et al., 2011). Among these paradigms, this research adopts the positivism paradigm as its chosen research philosophical design for three reasons.

First, unlike interpretivism and critical realism, the positivism paradigm believes in a stable social reality that exists independently from the social actors who construct it as well as from those (e.g., researchers) who observe it (Bryman et al., 2007). It views reality as a set of objective entities that can be observed, described, and tested using quantitative variables (Saunders et al., 2015; Matthews, 2010). Such a view algins with the researcher view of mHealth technology as a stable reality that is external and independent from its social actors (potential adopters). Such a view perceives mHealth technology as a stable phenomenon that cannot be freely changed or eliminated from the real world despite changes in its social actors. For example, even if changes occur in potential adopters, these changes cannot change the reality of the existence of mHealth apps as a healthcare service. Accordingly, mHealth apps are now an objective entity in the structure of reality and therefore to understand this objective reality, this research needs to adopt an objective stance to investigate the objective entities underlying potential adopters acceptance of mHealth services.

Second, positivism is a preferred choice when the aim of the study is to provide a comprehensive understanding of the underlying entities and mechanisms constituting a social phenomenon (Holden and Lynch, 2004; Saunders et al., 2015; Wynn and Williams, 2012). To understand reality, positivism apply highly structured research designs that rely on formal predefined propositions, quantifiable measures of variables, quantifiable data analysis methods, and large numbers of participants as a strategy for knowledge inquiry (Orilkowski and Baroudi, 1991). The prime aim of positivism research is to validate and confirm a set of predefined propositions to develop a law-like generalized knowledge (Neuman, 2003). Given that the main aim of this research is to provide a comprehensive understanding of potential adopters mHealth acceptance from a trust-anxiety perspective, such an aim thus requires the adoption of a neutral position by excluding researchers' personal views and interpretations from the studied phenomenon to achieve unbiased conclusions by employing objective data collection and analysis techniques. Therefore, this research has selected positivism as its chosen philosophical research design since it aligns with the research aim.

Third, positivism paradigm was also selected based on the investigated research questions as recommended by Saunders et al. (2015). Saunders et al. (2015) state that the selected research paradigm should be chosen based on the research questions investigated in the study. As noted in Section 1.4 in the introduction chapter, this study questions the nature of potential adopters' mHealth acceptance behaviour; for example, whether individuals mHealth acceptance behaviour is a matter of potential adopters trust and anxiety and goes a step further by questioning the factors affecting potential adopters trust and anxiety when accepting mHealth services for the first time. Such research questions in return require the use of predefined hypothesized relationships and quantifiable data measures/analysis techniques to understand individuals mHealth acceptance behaviour from a trust-anxiety perspective.

4.2 Approaches to Knowledge Inquiry

Before discussing the approaches to knowledge inquiry, it is important to first understand the meaning of research in its scientific terms. According to Babbie (1998), research is a systematic and organized way of knowledge inquiry. The purpose of research is "to discover laws and postulate theories that can explain natural or social phenomena, or in other words, build scientific knowledge" (Bhattacherjee 2012, p. 3). According to Bhattacherjee (2012), when conducting scientific research, knowledge inquiry usually takes one of the following forms: inductive or deductive.

In the inductive form, the process of knowledge inquiry usually starts by the collection of facts and evidence that explores the phenomenon, the discovery of themes and patterns, and ends by the development of a new or modified theory (Saunders et al., 2015). According to Bhattacherjee (2012), the main goal of inductive research is to infer the theoretical concepts and patterns underlying the explored phenomenon based on a set of empirical observations. Therefore, this form of research inquiry is often associated with the interpretivism paradigm, according to Bryman and Bell (2003).

In the deductive form, the process of knowledge inquiry usually starts with the creation of the theory, the formulation of hypotheses, the collection of facts and evidence, and ends up with the examination of the formulated hypotheses (Ghauri et al., 2010). In this form of knowledge inquiry, a theory is created based on existing theories and knowledge to drive its concepts and draw its hypotheses (Saunders et al., 2015). The goal of deductive research is then to confirm/reject the set of hypothesized relationships among the proposed concepts using new empirical data (Bhattacherjee, 2012). Therefore, this form of knowledge inquiry is often linked with the positivism paradigm (Bryman and Bell, 2003).

Considering the positivism paradigm adopted for this research, the deductive approach is thus recognized as the most appropriate research design for conducting this study especially as it lines up with the ontological, epistemological, and methodological assumptions held by positivism paradigm about knowledge development. Moreover, the deductive process of creating a theory, formulating its hypotheses, and examining its effectiveness has been adopted by many researchers in mHealth acceptance literature when inquiring about the factors affecting individuals' acceptance of mHealth services (Mou et al., 2018; Houqe et al., 2017; Deng et al., 2014; Meng et al., 2019). Besides this, in the field of information systems, psychology, and social psychology, there are many well-established theoretical concepts and theoretical frameworks that can be applied to the area of mHealth acceptance to explain individuals' behaviors from a trust-anxiety perspective. Therefore, the deductive approach to knowledge inquiry can provide a useful framework to guide the development process of the entire research.

4.3 Research Methods: Qualitative and Quantitative

Following on the discussion from previous sections, this section will further discuss the selected research method for this study. Research methods are generally used to reflect the type of data collection and analysis techniques used in the development of knowledge. Generally, there are two major methodological approaches underpinning data collection and analysis techniques in human and social science research, known as, qualitative and quantitative methods (Crewsell, 1994; Saunders et al., 2003). Qualitative research methods are commonly used to describe the set of data collection and analysis techniques that utilize natural human languages (e.g., words, phrases, and expressions) as a strategy to investigate reality. On the other hand, quantitative research methods are used to describe the set of data collection and analysis methods that adopt the language of numbers as a strategy to investigate reality.

Among these research methods, this study adopts quantitative methods as its chosen approach for collecting and analyzing the research data for two reasons. First, unlike qualitative methods, quantitative methods employ highly structured data collection (e.g., survey) and analysis (e.g., multiple regression analysis) techniques when inquiring about reality as it assumes that social reality can be measured using numerical data (Saunders et al., 2003). Therefore, quantitative research methods are believed to be most suitable for research problems that aim to identify the entities and mechanisms governing an individual’s perceptions, feelings, and/or behaviors (Saunders et al., 2003). As stated previously in Section 1.3 in the introduction chapter, the main objective of this study is to provide a comprehensive understanding of potential adopters’ mHealth acceptance behavior from a trust-anxiety perspective. Such an objective, therefore, requires the identification of the key factors underlying individuals mHealth acceptance behavior. Accordingly, quantitative methods have been chosen as they provide researchers with standardized quantifiable measures and data analysis techniques to capture the factors constituting an individual’s behavior (Cooper and Schindler, 2014). Second, according to Bryman et al. (2014), quantitative methods are guided by the objective paradigm and deductive approach, which is consistent with the research philosophy and the knowledge inquiry approach adopted in sections 4.1.4 and 4.2.

4.4 Research Design

As shown in Figure 5.1, the research design of this study is finalized after three main stages, mainly the exploration, assessment, and validation. In the exploration stage, an extensive literature review has been conducted on mHealth acceptance, trust, and anxiety research to build the foundation for the entire research. The extensive literature review was primarily concerned with reviewing the current research on mHealth acceptance behavior from a trust and anxiety perspective to identify the current gaps in mHealth acceptance literature, as described in Chapter 2. The identified gaps were then used in the development of research aim and questions. The exploration stage also includes the development of the research model and its proposed hypotheses, as shown in Chapter 3.

In the assessment stage, the main focus is placed on the discussion of the appropriate research methods used for assessing the research hypotheses proposed in the exploration stage. In other words, this stage is primarily concerned with selection of an appropriate research philosophical paradigm, knowledge inquiry approaches, and data collection/analysis methods and procedures. As shown in Figure 5.1, this research adopts online self-administered survey as its main data collection technique for this research. A pilot study (n= 64) is conducted for examining the appropriateness of the decided measures as shown in Section 4.5. The aim of the pilot study was to test the reliability and validity of the instruments used in this study before applying them on a larger sample. The results of the pilot study have verified the reliability and validity of the chosen instruments contributing to the formation of the final version of the online self-administered questionnaire survey.

In the validation stages, the main focus is placed on the examination and assessment of the proposed research model using quantitative data analysis methods. In this stage the data was collected via the revised online questionnaire based on the results of the pilot study. The empirical analysis was conducted on a total of 385 responses in Saudi Arabia and 507 responses in the United Kingdom, shown in Chapter 5, to assess the hypotheses proposed in the research model. The results of the assessments are discussed in further detail in Chapter 5.

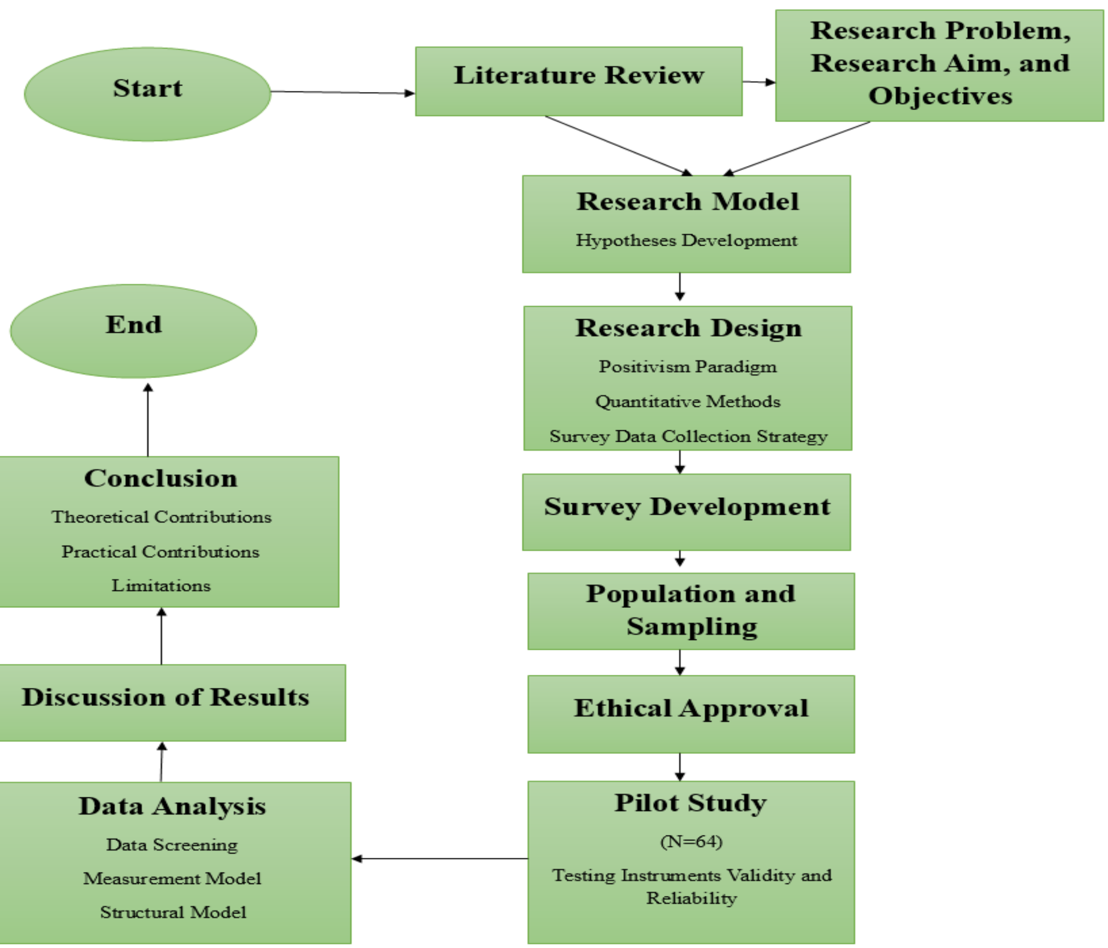

Figure 4.1 Research Design

4.5 Measurement Scale Development

4.5.1 Relative Advantage

Relative advantage is defined as the degree to which an innovation is perceived as being better than its precursor (Rogers, 2014). Given the emergent nature of mHealth services as an alternative channel to regular doctor visits, this thesis defines relative advantage as the degree to which the use of mHealth services is perceived as superior to the idea of in person doctor visits. Relative advantage is used to measure the benefits the new technology provides to its adopters compared to the idea it replaces it. Accordingly, in this thesis, relative advantage is used to measure the benefits mHealth provides to its adopters in terms of its convenience, health management control, speed to access healthcare services, and costs. The measures of relative advantages were adopted from Kim et al. (2009) and Yang et al. (2012) studies and it has been modified to fit mHealth context.

Table 4.1 Relative Advantage Measurement

Construct	Item
Relative Advantages	RA1. Using mobile health to receive healthcare services is more convenient than regular doctor visits.
	RA2. Mobile health enables me to reach physicians more quickly than regular doctor visits.
	RA3. Mobile health provides me with greater control over my health management than regular doctor visits.
	RA4. Overall, mobile health is more useful for receiving healthcare services than regular doctor visits because I am less limited by location, time, and transportations.

Adopted from (Kim et al., 2009; Yang et al., 2012)

4.6.2 Ease of Use

Ease of use is used to reflect the degree to which an individual believes that the use of mHealth service would not require a lot of efforts. (Davis, 1998). Modified to the prior initial interaction stage, ease of use items is used to reflect the ease of configuring and using mHealth services for the first time. The measurement scale of ease of use was adopted from the studies of Guo et al. (2017), Lee et al., 2009, and Kim et al. (2010).

Table 4.2 Ease of Use Measurement Scale

Construct	Item
Ease of Use	EOU1. It would be easy for me to configure (e.g., install, create an account) mobile health on my mobile device.
	EOU2. Learning how to operate mobile health to conduct healthcare transactions like booking an appointment, consulting a physician, making a payment, etc. would be easy for me.
	EOU3. I think that the use of mobile health would not require a lot of mental effort.
	EOU4. Overall, I think that mobile health would be easy to use.

Adopted from (Guo et al., 2017; Lee et al., 2009; Kim et al., 2010)

4.6.3 Trialability

Trialability refers to the degree to which an innovation can be experimented with before adoption (Rogers, 2014). The conceptualization of trialability is used to capture the availability of innovation functions for trial before one fully adopts or utilizes the innovation. Modified to the pre-initial interaction stage and extended to mHealth context, this study defines trialability as the extent to which an individual wants mHealth services to be available for trial before being fully utilized (Tan and Teo, 2000; Al-Jabri and Sohail, 2012) to capture the extent to which potential adopters want mHealth services to be available for personal trial before making a full use of mHealth service. The items in the measurement scale are used to reflect potential adopters desire to have mHealth services available for experiments before being fully utilized. These items have been adopted from the studies of Karahanna et al. (1999), Tan and Teo (2000), Al-Jabri and Sohail (2012) in which they were modified to fit with mHealth context.

Table 4.3 Trialability Measurement Scale

Trialability	TR1. Before deciding whether to use mobile health, I prefer trying it out first for once.
	TR2. I want to use mobile health on a trial basis to see what it can do for me.
	TR3. I want mobile health to be available for me to try without me having to provide personal information first.

Adopted from (Karahanna et al., 1999; Tan and Teo, 2000; Al-Jabri and Sohail, 2012)

4.6.4 Facilitating Conditions

Facilitating conditions are used to reflect the degree to which an individual believes that organizational and technological infrastructure exist to support the use of mHealth services (Venkatesh et al., 2003). The conceptualization of facilitating conditions is used to capture the external factors related to technology use environment that makes an act easy to do. Modified to the pre-initial interaction stage and extended to mHealth context, facilitating conditions in this thesis is used captures the extent to which potential adopters believe that they will have required information resources and the needed help and support to use mHealth services. The items in the measurement scale are used to reflect potential adopters' perceptions about the availability of mHealth use instructions, a technical support center, and help and support. These items have been adopted from the study Venkatesh et al. (2000) in which they were modified to fit with mHealth context.

Table 4.4 Facilitating Conditions Measurement Scale	
Facilitating Conditions	FC1. The use of mobile health would be compatible with my current experience with other mobile apps.
	FC2. A technical support center would be available for assistance when I have difficulties in using mobile health.
	FC3. A set of use instructions would be available for me while I am using mobile health.
	FC4. I could get help from others when I have issues in using mobile health.

Adopted from (Venkatesh et al., 2000)

4.6.5 External Social Influence

External social influence is used to reflect the extent to which an individual's mHealth use is influenced by information from media and nonpersonal sources (Bhattacharjee, 2000; Roger, 1995; Song, 2016). The conceptualization of external social influence is used to capture the effect of media reports and advertisements on mHealth acceptance. The items of the measurement scale have been adopted from the study Bhattacharjee (2000) and Song (2016) in which they were modified to fit with mHealth context.

Table 4.5 External Social Influence Measurement Scale	
External Social Influence	ESI1. I read/saw media reports suggesting that mobile health was a good way to receive healthcare services.
	ESI2. Media advertisements consistently recommend the use of mobile health.
	ESI3. Information from media would influence my opinion about using mobile health.

Adopted from (Bhattacharjee, 2000; Song, 2016)

4.6.6 Interpersonal Social Influence

Interpersonal social influence is used to reflect the extent to which an individual mHealth use is influenced by the opinions of their friends, family, and other adopters known to the potential adopter (Bhattacharjee, 2000, Song, 2016). The conceptualization of external social influence is used to capture the effect of peers on mHealth acceptance. The items of the measurement scale have been adopted from the studies of Bhattacharjee (2000), Song (2016), Venkatesh et al. (2000) in which they were modified to fit with mHealth context.

Table 4.6 Interpersonal Social Influence Measurement Scale

Interpersonal Social Influence	ISI1. People I know (e.g., family, friends, peers, colleagues) think that using mobile health to receive healthcare services is a good idea.
	ISI2. People whose opinion I value would prefer that I use mobile health for managing my health.
	ISI3. People I know have recommended that I should try mobile health.

Adopted from (Bhattacharjee, 2000; Song, 2016)

4.6.7 Trust in mHealth Service Provider

Trust in mHealth service provider is defined as the extent to which individuals believe in the competence, benevolence, and integrity of mHealth service provider. The conceptualization of trust in mHealth service provider is used to capture the individuals’ perceptions of service provider’s honesty in keeping their promises and commitments, service provider’s ability and knowledge in providing healthcare services, and service provider’s caring behavior. The items of the measurement scale have been adopted from the study of McKnight et al. (2002) in which they were modified to fit with mHealth context.

Table 4.7 Trust in mHealth Service Provider Measurement Scale

Trust in mHealth Service Provider	Competence	TSPC1. Mobile health service provider would be skillful and able to provide its healthcare services remotely.
		TSPC2. Mobile health service provider would provide medical advice very effectively.
		TSPC3. Mobile health service provider would be fully qualified in providing healthcare services.
	Benevolence	TSPB1. Mobile health service provider would be interested in my well-being, and not just in serving itself.
		TSPB2. If I required help, mobile health service provider would do its best to help me.
		TSPB3. I believe that the mobile health service provider would be concerned about what is best for me.
	Integrity	TSPI1. Mobile health service provider would provide me with factual information about my health.
		TSPI2. Mobile health service provider would honor any commitments it makes.
		TSPI3. I expect mobile health service provider to be honest with me.

Adopted (McKnight et al., 2002)

4.6.7 Trust in mHealth Service

Trust in mHealth services is used to reflect the extent to which individuals believe in the functionality and reliability of mHealth services. The conceptualization of trust in mHealth services is used to capture individuals' beliefs about the availability of the required functions for their tasks and reliability of the services provided through mHealth services. The measurement scale of trust in mHealth services has been adopted from the study of McKnight et al. (2011) in which they were modified to fit with mHealth context.

Table 4.8 Trust in mHealth Service Measurement Scale

Trust in mHealth Service	Reliability	TT1. Mobile health would be a reliable piece of application.
		TT2. Mobile health would not fail me.
		TT3. I can depend on mobile health to receive my healthcare services remotely.
	Functionality	TTF1. Mobile health would have the required features for my tasks (e.g., for booking appointments, ordering prescriptions, reviewing medical records, consulting physicians, etc.).
		TTF2. Mobile health would have the necessary technological functionality to receive healthcare services.
		TTF3. Mobile health would be able to do what I need.

Adopted from (McKnight et al., 2011)

4.6.8 Visibility

Visibility is the degree to the use of mHealth services is apparent to an individual in their social surroundings (Moore and Benbasat, 1991). The conceptualization of visibility is used to capture the individual's beliefs about the usability of mHealth services among the members of their social systems. The items have been adopted from the study of (Moore and Benbasat, 1991) in which they were modified to fit with mHealth context.

Table 4.9 Visibility Measurement Scale	
Visibility	VS1. In my surroundings, I heard/read that others have used mobile health to manage their health.
	VS2. I have heard/read about what others can do using mobile health.
	VS3. It is easy for me to notice others in my surroundings using mobile health to receive healthcare services.
	VS4. Mobile health is commonly used in my surroundings.

Adopted from (Moore and Benbasat, 1991)

4.6.9 mHealth Use Anxiety

mHealth use anxiety is a psychological condition reflecting the fear an individual experiences when faced with the possibility of losing one's confidential information when using mHealth services. The conceptualization of mHealth use anxiety is used to capture individuals' fears of making mistakes, losing control of their information, and their overall fear of using mHealth services. The items of the measurement scale have been adopted from the studies of Meuter et al. (2003) and Hwang et al. (2007) in which they were modified to fit with the context and conceptualization mHealth use anxiety in this study.

Table 4.10 mHealth Use Anxiety Measurement Scale	
mHealth Use Anxiety	MXU1. I would hesitate using mobile health due to the fear of making costly mistakes that I cannot correct.
	MXU2. When using mobile health, I fear that I might lose my personnel information.
	MXU3. When using mobile health, I fear that the service provider might share my personal information with others without my permission.
	MXU4. I feel apprehensive about using mobile health to receive healthcare services remotely.

Adopted from (Meuter et al., 2003; Hwang et al., 2007)

4.6.10 mHealth Acceptance

mHealth acceptance is defined as extent to which individuals intend to use mHealth services (Ajzen et al., 1990; Davis et al, 1998; Venkatesh et al., 2003). The conceptualization of mHealth acceptance is used to capture subjective tendency to use mHealth services. The items of the measurement scale have been adopted from the studies of Alam et al. (2021), Guo et al. (2016) Mou et al. (2020) in mHealth context.

Table 4.11 mHealth Acceptance Measurement Scale

mHealth Acceptance	AC1. I plan to install mobile health on my mobile device in the future when I have the chance. AC2. Given that I had access to mobile health on the app store, I predict that I would use it. AC3. Assuming that I had access to mobile health on my device, I intend to use it within the next six months.

Adopted from (Alam et al. 2021; Guo et al., 2016; Mou et al., 2020)

4.6 Scale Used for Measurement

A seven-point Likert scale is adopted in this research. This means that each item is measured on a seven-point scale ranging from 1 (strongly agree) to 7 (strongly disagree). There are several reasons for using a seven Likert scale instead of others. First of all, a seven Likert scale provides researchers with more reliable responses since respondents have more choice options to choose from when answering the questionnaire (e.g., three positive options and three negative options). Furthermore, a seven Likert scale increases the validity and reliability of the measurement scale of each construct since it increases the spread of the data around the mean (Dawes, 2008). Moreover, a large amount of literature in IS research has been shown to support the use of seven Likert scale in their research (e.g., Venkatesh et al., 2003; Bhattacherjee, 2000; Meuter et al., 2003; Davis, 1998; Lin, 2011; McKnight et al., 2002). Additionally, the questionnaire survey includes some demographic information, covering factors, such as gender, age, education, and income. These factors are measured through nominal scales (see Appendix A).

4.7 Research Population and Sampling

According to Cooper et al. (2014), research population is the full set of cases that a researcher intends to study and investigate. Since it is challenging to reach and study each case in the targeted population, a representative "sample" can therefore effectively resemble the entire population at large (Bryman et al., 2016). According to Saunders et al. (2019), a "sample" is used to reflect the subset of cases selected out from the targeted research population. Researchers choose a certain number of samples from the entire population to make statistical inferences and draw conclusions that can be applied to the larger population from which the sample was drawn (Bryman et al., 2016). Given that one of the objectives of this research is to conduct a comparative study between the countries of the United Kingdom (UK) and Saudi Arabia (SA), thus, in this research the targeted population from both countries is specifically the potential adopters of mHealth services who have not yet experienced or used mHealth services before, while the sample is narrowed down to those who own a tablet or smartphone and have not used an mHealth application to receive their healthcare services remotely yet. The targeted sample in this study was recruited by specifying the target population that this study intends to examine their behavior (e.g., research participants with a smartphone or tablet and has not yet used an mHealth application that provide virtual health care services before) in the advertisement letter distributed to research participants in Saudi Arabia and the United Kingdom.

There are two approaches to sampling in social science research, namely, probability and non-probability sampling. With probability sampling, each unit in the targeted papulation has a known chance, with equal probability, of being selected in the chosen sample (Ghauri et al., 2010). Unlike probability sampling, non-probability sampling is a non-random sampling technique, which means that the probability that each case is selected from the targeted population is unknown (Ghauri et al., 2010). However, one of the main drawbacks of probability sampling is that it requires the identification of a reliable sampling frame (Saunders et al., 2019). A sampling frame is a physical representation of all the units from which the research sample will be selected. Due to the emergent nature of mHealth services, it is nearly impossible to outline a robust list of all potential mHealth adopters from SA and UK to draw its samples especially as the numbers of mHealth service adopters change constantly. While the key advantage of probability sampling relies on the representative nature of the sample, this can also be boosted by non-probability sampling (Saunders et al., 2019). Therefore, this research selects non-probability sampling as its main sampling technique since it is less restricted in terms of its sampling procedures.

Yet, non-probability sampling is not without limitations. With non-probability sampling, it is difficult to estimate sampling error (Bryman et al., 2016). Sampling error occurs when the selected cases significantly differ from the population from which they were selected (Bryman et al., 2016). This in turn may lead to problems such as sampling bias, which may constrain the representative nature of the sample to its entire population (Bhattacherjee, 2012). In order to mitigate sampling error, this research has limited its selected samples to those who had never used mHealth services before in SA and the UK to ensure that the chosen respondents can sufficiently represent its targeted population of mHealth potential adopters in both countries. In addition, this research utilizes a large number of samples as another strategy to minimize sampling error.

Under the umbrella of non-probability sampling, there are four main sampling methods that can be used for selecting research samples, namely, quota, snowball, purposive, and convenience sampling. Among these sampling methods, this research chooses convenience sampling as its main strategy for collecting the research data. Convenience sampling is a data collection technique that selects research units or respondents based on their availability and accessibility to the researcher (Sandras et al., 2003). It is recognized as one of the cheapest, easiest, and fastest techniques for selecting research participants in social science research (Bryman et al., 2016). Compared to quota sampling, convenience sampling applies less restrictions in terms of the selection research cases. For example, in quota sampling, the targeted population is segmented into subgroups based on certain predefined characteristics (e.g., age, gender, religion), which serves as a framework for selecting research sample units (Bhattacherjee, 2012), which shows considerable difficulties in contexts that lack information about the targeted population of mHealth potential adopters in Saudi Arabia and the United Kingdom. In addition, unlike convenience sampling, the selection of research units in snowballing and purposive sampling can lead to sampling issues like sampling bias (Bryman et al., 2016; Sandras et al., 2003). For example, in purposive sampling, the selection of research units depends heavily on the researcher’s subjective inference of the degree to which the selected unit can represent its targeted population. On the other hand, in snowballing sampling, research units are primarily selected through a network of referrals, in which the initial group of participants serves as the main method for identifying later respondents who usually share similar interests and characteristics. Due to the advantages of convenience sampling posits over other sampling techniques, this research uses convenience sampling as its main sampling technique to draw its research samples from Saudi Arabia and the United Kingdom.

4.7.1 Units of Analysis and Sample Size

Unit of analysis is the level at which the data will be analyzed; for example, whether that data will be analyzed on the individual, group, organization, country, or technological level (Sekaran et al., 2016; Bhattacherjee, 2012). The selection of the unit of analysis primarily depends on the purpose and interest of the study. In this thesis, individuals are selected as the research unit of analysis since the aim of the research is to provide a comprehensive understanding of individuals' mHealth acceptance behavior from a trust-anxiety perspective. Such understanding can only be achieved by collecting data from the level of the targeted population. Therefore, this research selects individuals as its main unit of analysis.

Selecting an appropriate sample size is an essential step for extracting a sample from the targeted population. Insufficient sample size is more likely to lead to improper solutions and less accurate parameters (Hair et al., 2017). On the other hand, a large sample size that is larger than the estimated size increases the costs, time, and efforts used to collect the data (Bryman, 2015; Gill et al., 2010). Therefore, an appropriate sample size is required to get trustworthy and reliable results (Sandras et al., 2003; Collis et al., 2003; Sekaran et al., 2016). The selection of an adequate sample size depends heavily on the statistical analysis technique used to analyze the data. In this study partial least squares structural equation modelling (PLS-SEM) is used for analysing the collected research data, as discussed in further details in Section 4.13. Accordingly, for partial least square (PLS) path modeling estimations, a rule of thumb suggests that the sample size should be equal to the larger one of the following (Barclay, Higgins, and Tompson, 1995):

(1) ten times the maximum number of paths targeting at any construct of the measurement model; or (2) ten times the largest number of structural paths targeting at a particular construct in the structural model. Since the largest construct in this model contains at most 9 items (e.g., trust in mHealth service provider) and the construct with the largest number of paths pointing at it consists of 4 structural paths (e.g., mHealth acceptance), therefore, the least acceptable sample size for conducting a robust PLS path modeling estimation is 90 research participants.

4.8 Research Ethics Consideration

Consideration of ethical issues is one of the important early steps in research studies that involve the study of consumer behavior (Ghauri et al., 2010). Anonymity and confidentiality are two central ethical issues surrounding research studies that involve human participants, which should be addressed during and after the collection process of research data to protect research participants from any harm and misrepresentation (Cooper and Schindler, 2014; Bryman and Bell, 2015). Research studies that neglect anonymity and confidentiality issues during the collection process of their research data are more likely to experience poor response rates with misleading responses (Sekaran and Bougie, 2016; Cooper and Schindler, 2014), which makes it difficult for researchers to collect reliable research data.

To ensure that this research is ethically conducted, an ethical approval was obtained from the University Research Ethics Committee (UREC) at the University of Manchester prior to recruiting research participants. An information sheet was attached to both the recruiting and cover letter to inform research participants about the purpose of the research and the confidentiality of their collected demographic data and responses. Research participants were also informed in the cover letter that their participation in the study was voluntary and that they had the right to withdraw from the study at any point of time during their participation in the online survey. They were also informed that all provided information will be kept confidential at all times and that the results of this study will be reported in aggregated anonymous ways, and it will be only used for academic purposes, as shown in Appendix A.

4.9 Data Collection Procedures

Based on the selected research philosophy, approach, and method, this research chooses surveys as its main data collection method for the following reasons. As a data collection technique, surveys are designed specifically to collect evidence in a systematic and standardized manner (Cooper and Schindler, 2014). The greatest strength of surveys lies in their highly structured design, in which they use a set of predefined questions and answers (e.g., multiple choice) as a strategy for collecting research data. Such a design is suitable for obtaining objective data. Therefore, surveys constitute one of the most effective tools for capturing cause-effect relationships (Ghauri et al., 2010). Besides this, surveys provide researchers with an inexpensive, quick, efficient, and accurate means for assessing the collected data (Zikmund, 2003). Surveys are primarily concerned with the collection of evidence to make statistical inferences from a fraction of the studied population to the entire population. In addition, surveys are one of the most powerful tools for capturing and measuring unobservable data such as beliefs, feelings, and behaviors (Bhattacherjee, 2012). Therefore, this research selects surveys as its main data collection strategy, as it is one of the preferred tools when the research aim is to understand the patterns and reasons causing individuals behavior (Larry et al., 2015). Similarly, the literature review shows that surveys are preferred as a data collection method when the study involves studying the factors constituting individuals mHealth acceptance behavior (Mou et al., 2021; Houqe et al., 2017; Deng et al., 2014; Guo et al., 2016).

There are two main approaches to surveys: self-administrated surveys and structured interviews (Cooper and Schindler, 2014). The main difference between the two techniques is that with self-administered surveys, the survey is primarily administered and completed by the respondents themselves. While in the latter, a trained interviewer is the main administrator of the survey, either in person or via a communication medium such as the telephone (Sandras et al., 2003). In this research, self-administrated surveys are adopted for four reasons. First, unlike self-structured interviews, self-administrated surveys are specifically designed to capture non-verbal responses from research participants (Bhattacherjee, 2012). Accordingly, one of the advantages of self-administrated surveys over structured interviews is that self-administrated surveys are less time- and resource-intensive than structured interviews (Cooper and Schindler, 2014). Second, online self-administered surveys are easy to design and quick to implement. Researchers can design their online self-administrated surveys through questionnaire tools such as Qualtrics.

These questionnaire tools not only provide a means for designing online self-administrated surveys, but they also support the distribution of these designed questionnaires through different online communication platforms (e.g., Whats App) and in different languages. Third, online self-administered surveys offer a great potential to reach a rich pool of research participants with different geographical locations and demographical backgrounds (Cooper and Schindler, 2014). Therefore, online self-administered surveys are considered as one of the most cost-effective and time-efficient ways to get access to hundreds or even thousands of respondents located in different geographical locations. Fourth, online self-administered surveys can increase the response rates of respondents since they represent one of the most convenient ways for answering research surveys (Ilieva, Baron, and Healey, 2002).

Yet, just like with other data collection tools, online self-administered surveys have some inevitable disadvantages. For example, one of the key concerns arising around online self-administered surveys is whether research respondents can represent their entire population (Ilieva, Baron, and Healey, 2002). Therefore, to increase the representative nature of collected responses, online self-administrated surveys were distrusted to research respondents with different demographical backgrounds (e.g., age, gender, income, and education) from different cities when recruiting research participants. Another concern surrounding online self-administered surveys is that with the absence of researcher presence, issues around understanding may arise when answering online self-administered surveys (Cooper and Schindler, 2014; Flaherty, Pearce, and Rubin, 1998). In order to ensure that respondents can accurately understand survey questions, the researcher has carefully designed the self-administered survey questions. In addition, the researcher has included a cover letter that states the research aim as well as an introduction section that clarifies the definition of mHealth services and some examples of available mHealth services in the market for each country respondent. The researcher has also left their contact details (e.g., email) in case research respondents had further questions about the survey.

The online self-administered surveys were designed using Qualtrics. Qualtrics was selected as a data collection tool for two reasons. First, it is free, and it supports the design of online questionnaires in both Arabic and English. Second, it is one of the trusted online survey platforms used by universities for academic research purposes. In Saudi Arabia, the link to the online survey was distributed to research participants from different backgrounds (e.g., age, gender, income, and education) and from different cities (e.g., Dammam, Dhahran, Medina, Jeddah, Maca, Riyadh) through the social media app "Whats App" and research participants were asked to share the online survey with their friends, family, and colleagues. On the other hand, in the United Kingdom, research data were collected with the assistance of a data collection company named Prolific. The online company survey has electronically distributed the survey to a panel of research participants living in the United Kingdom with different backgrounds and from different cities.

4.10 Survey Construction

The constructed online survey consisted of eight sections, as following:

- The first section was the cover letter. The cover letter was used to explain the purpose of the study and the anonymity and confidentiality of the collected responses as recommended by Bhattacharjee (2012). An information participants sheet was also attached to the cover letter to make sure that all participants were aware of the format by which the collected data will be reported and the places in which it will be reported in, and the role that research participants will play in the study.
- The second section was the introduction section. The introduction section was used to define the type of mHealth app used in this study to research participants. To ensure that all research participants were aware of the technology understudy, researchers in IS acceptance filed had always provided an introduction to the innovation understudy before measuring research subjects' responses (e.g., Davis et al., 1989, Morris and Venkatesh, 2000; Mou et al., 2021; Guo et al., 2016). Accordingly, in the introduction section, research participants were introduced to mHealth app (e.g., its definition, functions, and some examples of available mHealth services in the market) used in this study before filling out the survey. To ensure that only those who this research targeted had answered the survey, respondents were asked about the number of times they had used such mobile health services before. Only those who have not used such mHealth apps before were able to proceed with the rest of the survey.

- The third section was concerned with the questions related to research participants' demographic information. For example, their education level, age, gender, and income.
- The fourth section was concerned with the research questions related to mHealth use anxiety, trialability, relative advantage, ease of use, and facilitating conditions.
- The fifth section was concerned with the question related to visibility, interpersonal social influence, and external social influence.
- The sixth section was concerned with the question related to trust in mHealth service.
- The seventh section was concerned with the questions related to trust in mHealth service provide.
- The eighth section was concerned with the questions related to mHealth acceptance, as shown in Appendix A.

4.11 Pilot Study

Before administering the online survey to the targeted sample of research respondents, it is of great importance to first test the reliability and validity of the research instruments (items) used to measure the proposed research model constructs by conducting a pilot study (Bhattacharjee, 2012). The pilot study is usually conducted on a small subset of the targeted population. The sample size of the pilot study generally does not have a common range. Hunt et al. (1982), for example, recommended a sample size that ranges between 12 and 30 participants, while Emory and Cooper (1991) suggested using a larger sample size for the pilot study, especially as the accuracy of the results depends on the sample size used in the pilot study.

Accordingly, a pilot study was conducted on a total of 63 completed responses received from postgraduate students living in the United Kingdom who had never used an mHealth application that provides remote healthcare services before. The pilot study was distributed to postgraduate students through the social media app "Whats App" and by email through the PGR administrator at the University of Manchester. The purpose of the pilot study was to test the reliability and validity of the constructs used in the proposed model. This helped in detecting reliability, validity, and clarity issues before conducting the full scale of data collection.

The assessment of the constructs was conducted using SmartPLS version 3.9.9. The constructs were assessed in terms of their reliability, convergent validity, and discriminant validity. The results of the pilot study are discussed in further detail in Section 5.2 in the results chapter. Overall, the results showed acceptable levels of construct reliability and validity. Although interpersonal social influence and visibility constructs showed acceptable levels of discriminant validity, some of their instrument cross-loadings were above 0.70. Such high cross loadings suggest that these constructs might be viewed as similar by research participants, which might affect their discriminant validity when conducting the data collection at a larger scale. Therefore, the clarity of these two constructs was improved as follows: 1) Item ISI2 from the interpersonal social influence construct was rephrased from "People I know have thought that using mobile health to receive healthcare services was a good idea" to "People I know (e.g., family, friends, peers, colleagues) think that using mobile health to receive healthcare services is a good idea", 2) Item VS1 from the visibility construct was rephrased from "I have heard that others have downloaded mobile health on their mobile devices to manage their health" to "In my surroundings, I heard/read that others have used mobile health to manage their health", 3) Item VS3 from the visibility construct was rephrased from "It is easy for me to notice others in my community using mobile health to receive healthcare services" to "It is easy for me to notice others in my surroundings using mobile health to receive healthcare services.", 4) Item VS4 was added to the visibility measurement scale as an overall (general) measure: "Mobile health is commonly used in my surroundings".

4.12 Translation of the Survey

The survey was originally designed in English, with its content being carefully evaluated by several academics from the University of Manchester in the United Kingdom and King Fahd University of Petroleum and Minerals in Saudi Arabia. The survey was then pilot tested on 63 research participants. After that the online survey was translated by a professional translation service in Saudi Arabia by an academic who holds a Ph.D. degree in linguistics. To verify the quality of the translated survey, an academic from King Fahd University of Petroleum and Minerals who is proficient in both English and Arabic conducted a back translation from English to Arabic language. The researcher then compared the translated Arabic version obtained from the professional translation service with the back-translated English version to verify its quality. After that, the verified Arabic version of the survey was then reviewed by a professional who holds a bachelor's degree in Arabic Studies to ensure that the content of the items can be easily understood by Arabic respondents from different backgrounds. This process enabled the identification and modification of ambiguous expressions within some of the items' content. Following these modifications, the Arabic survey version was pre-tested by research respondents who are professional in Arabic and English languages to verify its clarity and quality.

4.13 Data Analysis Procedures

To test and validate the proposed research model, this research adopts structural equation modeling (SEM), a second-generation multivariate analytical technique, as its main method for analysing the collected research data. While both SEM and first-generation analysis techniques (e.g., cluster analysis, logistic regression, multiple regression, and exploratory factor analysis) belong to the same family of multivariate analytical techniques, SEM is superior to the latter in terms of its precise estimations when the analysis involves latent variables with multiple indicators (Gefen et al., 2011). Unlike first-generation techniques, SEM permits unobserved variables (latent variables) to be measured with its observed variables (indicators) at the same time (Hair et al., 2017). This in turn allows SEM to take into account the measurement errors (i.e., the differences between measures and the construct being measured) of the observed variables when estimating the interplay between the proposed theory and the collected empirical data. Furthermore, SEM enables the measurement model to be analysed simultaneously with the hypothesized causal paths in the proposed structural model (Gefen et al., 2000; Gefen et al., 2011). This in turn provides researchers with a better estimation of the causal relationships among latent variables compared to those provided by first-generation techniques (Chin et al., 2008; Gefen et al., 2011; Gefen et al., 2000). Due to its estimation strength, this research therefore chooses SEM over first-generation analysis techniques for analysing the research data.

There are two types of SEM techniques in information systems research: covariance-based structural equation modeling (CB-SEM) and partial least squares structural equation modeling (PLS-SEM) (Chin et al., 2008). According to Hair et al. (2010), the objective of CB-SEM is to minimize the differences between the observed and estimated covariance matrix, using software packages such as AMOS, LISREL, MPlus, and EQS. On the other hand, the objective of PLS-SEM is to maximize the explained variance in the dependent variables, using software packages such as Smarts PLS, PLS Graph, and VisualPLS (Hair et al., 2014). In this study, PLS-SEM is used as the main method for analysing the collected research data for three reasons.

First, PLS-SEM is a preferred choice when the objective of the research is to predict key target constructs, identify key drivers of a construct, extend a theory, or develop a new theory (Hair et al., 2014). Given that this research is exploratory in its nature, in which it aims to predict the factors underlying potential adopters' acceptance of mHealth services from a trust-anxiety perspective, such objective is therefore can be achieved using PLS-SEM. This is because PLS-SEM is a causal-predictive data analysis technique that emphasizes prediction when estimating statistical models. In other words, PLS-SEM is designed specifically to provide causal explanations when estimating the relationships among latent variables in the proposed research model (Wold, 1982). Second, one of the advantages of PLS-SEM is that it imposes less restrictions in terms of the number of items used to measure a latent variable and the distribution assumptions on data (Afthanorhan et al., 2013; Hair et al., 2017). For example, PLS-SEM permits researchers to work with non-normally distributed data and to run statistical estimations on constructs with single measurement item (Hair et al., 2017). Third, another advantage of PLS-SEM relies on its ability to estimate complex models with many constructs and structural paths (Risher et al. 2018). As noted previously in section 3.1, the proposed research model is relatively complex. It includes 11 constructs and 19 hypothesized structural paths. Accordingly, this study chooses PLS-SEM as its main method for testing and validating the proposed research model since it is suitable for analyzing complex research models.

4.14 Chapter Conclusion

To sum up, this chapter elaborates on the research design used to conduct this study. As discussed earlier, this study adopts a positivism paradigm, a deductive approach, a quantitative technique, and a survey method for collecting the research data. Data analysis chosen technique and ethical consideration is also discussed in this chapter. This chapter lays the foundation for the next chapter where data analysis is conducted and presented in detail.

Chapter 5: Research Results

The proposed research model in Chapter 3 needs to be evaluated in terms of its validity, reliability, and significance. This chapter, therefore, consists of six sections to discuss the results of the evaluated proposed research model. Section 5.2 is used to introduce the path model implemented in the SmartPLS software, which consists of the measurement model and the structural model. Section 5.3 is used to discuss the results of the pilot study. Section 5.4 is used to describe the data cleaning and screening processes used in this study, which involved the deduction and identification of missing values, outliers, data normality, response bias, multicollinearity, factor loadings, and demographic information of research participants. Section 5.5 was devoted to analyzing the proposed research model in terms of the validity and reliability of the measurement model and the significance of the structural model. Section 5.6 serves as a summary of this chapter.

5.1 The PLS-SEM Path Model

The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM has been proven to be effective in answering a set of interrelated research questions in a single, systematic, and comprehensive manner. In PLS-SEM, the path model, a diagram that connects latent variables based on theory and logic, is made up by two major components, namely, the measurement model (also known as the outer model) and the structural model (also known as the inner model) (Hair et al., 2017). The measurement model is primarily used to describe the relationships between latent variables (constructs) and their set of indicators, while the structural model is used to describe the relationships among latent variables (Hair et al., 2017). The strength of PLS-SEM relies on its ability to test and validate the path model by integrating the measurement model with the structural model in the same analysis; thereby, accounting for a better estimation of the hypothesized relationships between latent variables since it considers the measurement error of indicators in the same analysis (Gefen et al., 2011).

Moreover, PLS-SEM can work effectively with complex models and non-normally distributed data as it makes no assumptions about the distribution of the population nor the scale of measurement used in measuring latent variables (Fornell and Bookstein, 1982; Cassel, Hackl, and Westlund, 1999; Chin, 1998; Hair et al., 2017). In addition, PLS-SEM can effectively handle measurement scales with different numbers of items as it aims to maximize the explained variance of the latent variable and minimize the unexplained ones (Afthanorhan, 2008). Such strength has made the use of PLS-SEM dominant among empirical IS research in general (Gefen et al., 2011) and mHealth acceptance research in particular (e.g., Mou et al., 2021; Fox et al., 2018; Alam et al., 2014).

The first step in creating a PLS-SEM path model is by building up the measurement model. The measurement model consists of the relationships among latent variables, as shown in blue circles, and the measurement items, as shown by yellow squares in Figure 5.1. The second step is to create the structural model by connecting latent variables using black arrows. These black arrows are a representation of the hypothesized relationships among latent variables. As shown in Figure 5.1, the structural model consists of 11 latent variables, namely, mHealth acceptance, mHealth use anxiety, trust in mHealth service, trust in mHealth service provider, visibility, trialability, ease of use, relative advantage, facilitating conditions, interpersonal social influence, and external social influence.

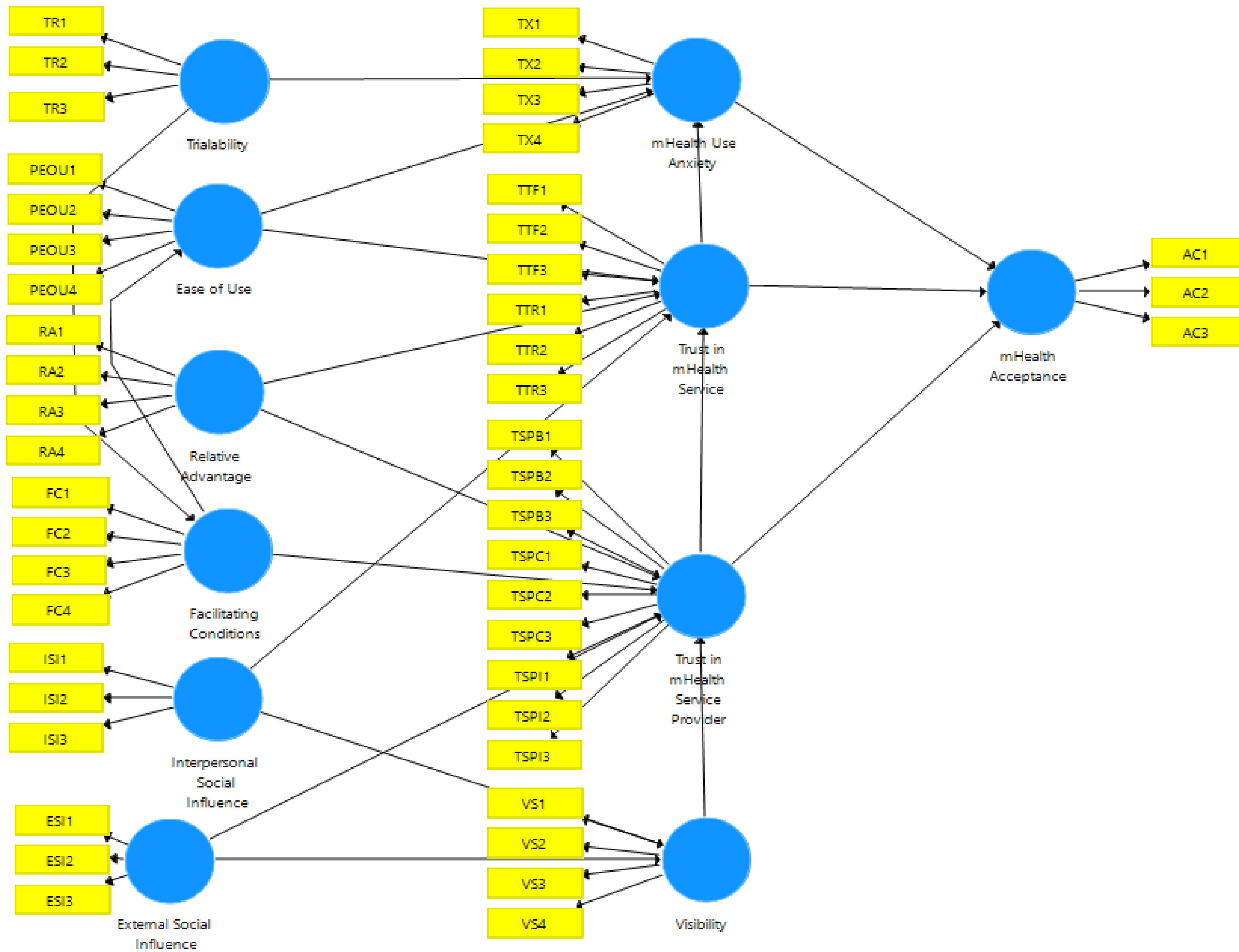

Figure 5.1 SmartPLS Path Model

5.2 Pilot Study Data Analysis

5.2.1 The Demographic Information of Participants

As discussed earlier in Section 4.11 in Chapter 4, the pilot study was conducted on a total of 64 valid online questionnaires that were collected from April 24th to May the 7th. Table 5.2 summarizes the demographic information of research participants involved in the study.

As shown in Table 5.2, 46.9% of the research participants were male, while 53.1% were female. Most of the research participants were in the age group of 25–34 (39.1%), followed by 18–24 (28.1%), 35–44 (20.3%), 45–54 (6.3%), 55–64 (3.1%), and ≥ 65 (3.1%). The education level of research participants ranged from bachelor's degree (26.6%) holders to diploma degree (21.9%) holders, high school graduate (17.2%) holders, doctorate degree (6.3%) holders, master's degree (3.1%) holders, to less than high school degree (3.1%) holders.

Table 5.2 Pilot Study Demographic Profile

	Number	**Percentage**
Gender		
Male	30	46.9
Female	34	53.1
Total	64	
Age		
18-24	18	28.1
25-34	25	39.1
35-44	13	20.3
45-54	4	6.3
55-64	2	3.1
≥ 65	2	3.1
Education		
Less Than High School	2	3.1
High School Graduate	11	17.2
Diploma Degree	14	21.9
Bachelor's degree	17	26.6
Master's degree	2	3.1
Professional Degree	0	0
Doctorate Degree	4	6.3

5.2.2 Measurement Validation

As discussed earlier in Section 4.11 in Chapter 4, the main aim of the pilot study was to validate the proposed model constructs in terms of their reliability, convergent validity, and discriminant validity. The assessment of the constructs was conducted using SmartPLS version 3.9.9. A confirmatory factor analysis was performed to assess factor loadings, as it can affect both construct reliability and discriminant validity. Hair et al. (2017) indicates that factor loadings equal to or greater than 0.60 can explain 60% of the variance in the construct, which is considered a very good level of variance. As shown in Table 5.4, all factor loadings were above the suggested threshold.

After assessing factor loadings, the reliability of measures was assessed using Cronbach's alpha and composite reliability tests. The results, as shown in Table 5.3, showed a good level of constructs reliability since all constructs Cronbach's alpha and composite reliability values were greater than the recommended cut-value of 0.70, as suggested by Hair et al. (2009) and Nunnally and Bernstein (1994).

Once the reliability of the measurement model was established, the next step was to assess the convergent and discriminant validity of the proposed model constructs. Convergent validity was assessed on the basis of the average variance extracted (AVE) values. According to Tabachnick and Fidell (2000), a value that is equal to or greater than 0.50 indicates a satisfactory level of convergent validity since the latent variable accounts for more than 50% of the variance in its indicators. As shown in Table 5.5, all AVE values were above 0.5, indicating a satisfactory level of convergent validity. On the other hand, discriminant validity was assessed using the Fornell-Larcker criterion and cross loadings. The Fornell-Larcker criterion suggests that each construct's AVE should be higher than its squared correlation with any other construct (Fornell and Larcker, 1981). As shown in Table 5.5, the diagonal elements are greater than corresponding off-diagonal elements, illustrating that the square root of each construct's AVE was greater than the correlation of the construct to other latent variables, thus, meeting the requirement for adequate discriminant validity. In addition to the Fornell-Larcker criterion, factor loadings serve as another way to evaluate discriminant validity (Chin, 1998). According to Chin (1998), an indicator's loading on its corresponding construct should be higher than all of its cross-loadings on other constructs. As shown on Table 5.6, all factor loadings, which are marked in bold, were larger than their cross loadings, thus representing a good level of discriminant validity. Yet, although the results showed that all factor loadings were larger on their corresponding constructs than their cross loadings on other constructs, the cross loadings of interpersonal social influence items on visibility and the cross loadings of visibility items on interpersonal social influence were both above 0.70. Such high cross loadings suggest that these constructs might be viewed as similar by research participants, which might affect their discriminant validity. Therefore, the clarity of these two constructs was improved as follows:

- Item ISI2 from interpersonal social influence construct was rephrased from “People I know have thought that using mobile health to receive healthcare services was a good idea” to “People I know (e.g., family, friends, peers, colleagues) think that using mobile health to receive healthcare services is a good idea.”
- Item VS1 from visibility construct was rephrased from “I have heard that others have downloaded mobile health on their mobile devices to manage their health” to “In my surroundings, I heard/read that others have used mobile health to manage their health”.
- Item VS3 from visibility construct was rephrased from “It is easy for me to notice others in my community using mobile health to receive healthcare services” to “It is easy for me to notice others in my surroundings using mobile health to receive healthcare services.”
- Item VS4 was added to the visibility measurement scale as an overall (general) measure: “Mobile health is commonly used in my surroundings.”

Table 5.3 Reliability Measures

	Cronbach's Alpha	Composite Reliability
mHealth Acceptance	0.927	0.953
Trust in Service Provider Benevolence	0.858	0.912
Trust in Service Provider Competence	0.866	0.918
Ease of Use	0.896	0.927
External Social Influence	0.783	0.871
Facilitating Conditions	0.742	0.835
Trust in mHealth Functionality	0.858	0.913
Trust in Service Provider Integrity	0.81	0.887
Interpersonal Social Influence	0.908	0.941
Relative Advantage	0.89	0.923
Trust in mHealth Reliability	0.836	0.901
mHealth Use Anxiety	0.805	0.869
Trialability	0.796	0.850
Visibility	0.858	0.912

Table 5.4 Factor Loadings

Items	Factors Loadings ≥ 0.60	Items	Factors Loadings ≥ 0.60
Trialability		**Trust in mHealth Service Provider Benevolence**	
TR1	0.793	TSPB1	0.867
TR2	0.970	TSPB2	0.885
TR3	0.641	TSPB3	0.892
Relative Advantage		**Trust in mHealth Service Provider Integrity**	
RA1	0.870	TSPI1	0.891
RA2	0.839	TSPI2	0.877
RA3	0.866	TSPI3	0.782
RA4	0.889	**Trust in mHealth Technology Reliability**	
Ease of Use		TTR1	0.859
EOU1	0.867	TTR2	0.862
EOU2	0.879	TTR3	0.880
EOU3	0.815	**Trust in mHealth Technology Functionality**	
EOU4	0.924	TTF1	0.914
Visibility		TTF2	0.863
VS1	0.890	TTF3	0.866
VS2	0.908	**mHealth Use Anxiety**	
VS3	0.841	MXU1	0.846
Interpersonal Social Influence		MXU2	0.800
ISI1	0.941	MXU3	0.671
ISI2	0.936	MXU4	0.835
ISI3	0.872	**mHealth Acceptance**	
External Social Influence		AC1	0.940
ESI1	0.888	AC2	0.919
ESI2	0.800	AC3	0.940

ESI3	0.807
Facilitating Conditions	
FC1	0.700
FC2	0.804
FC3	0.630
FC4	0.846
Trust in mHealth Service Provider Competence	
TSPC1	0.916
TSPC2	0.920
TSPC3	0.827

Table 5.5 AVE and Fornell-Larcker Criterion

	AVE	AC	TSPB	TSPC	EOU	ESI	FC	TTF	TSPI	ISI	RA	TTR	MXU	TR	VS
AC	0.871	**0.933**													
TSPB	0.776	0.395	**0.881**												
TSPC	0.790	0.434	0.699	**0.889**											
EOU	0.761	0.321	0.380	0.516	**0.872**										
ESI	0.694	0.428	0.473	0.206	0.145	**0.833**									
FC	0.562	0.444	0.548	0.648	0.598	0.305	**0.750**								
TTF	0.777	0.395	0.484	0.718	0.624	0.287	0.583	**0.881**							
TSPI	0.725	0.440	0.748	0.762	0.628	0.337	0.643	0.702	**0.851**						
ISI	0.841	0.503	0.351	0.149	0.131	0.704	0.358	0.277	0.232	**0.917**					
RA	0.750	0.476	0.405	0.592	0.445	0.11	0.589	0.582	0.571	0.224	**0.866**				
TTR	0.752	0.476	0.513	0.67	0.369	0.276	0.546	0.675	0.640	0.352	0.557	**0.867**			
MXU	0.625	-0.286	0.036	-0.077	-0.092	0.117	-0.011	-0.064	-0.010	-0.061	-0.262	-0.226	**0.791**		
TR	0.660	0.159	0.349	0.348	0.16	0.292	0.298	0.281	0.333	0.197	0.214	0.052	0.338	**0.813**	
VS	0.775	0.388	0.272	0.021	0.022	0.713	0.211	0.145	0.081	0.843	0.084	0.200	0.106	0.199	**0.880**

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MXU= mHealth Use Anxiety.

Table 5.6 Cross Loadings

	AC	EOU	ESI	FC	ISI	RA	TR	TSPB	TSPC	TSPI	TTF	TTR	MXU	VS
AC1	**0.940**	0.362	0.515	0.447	0.565	0.480	0.168	0.443	0.464	0.511	0.464	0.574	-0.293	0.465
AC2	**0.919**	0.300	0.337	0.363	0.364	0.411	0.19	0.347	0.354	0.362	0.283	0.265	-0.255	0.265
AC3	**0.940**	0.214	0.299	0.417	0.437	0.428	0.083	0.288	0.374	0.319	0.319	0.434	-0.242	0.312
EOU1	0.27	**0.867**	0.124	0.562	0.146	0.343	0.248	0.431	0.551	0.616	0.651	0.323	0.047	0.055
EOU2	0.244	**0.879**	0.055	0.455	0.028	0.366	0.091	0.204	0.37	0.518	0.521	0.332	-0.076	-0.073
EOU3	0.274	**0.815**	0.214	0.463	0.141	0.343	0.087	0.221	0.302	0.392	0.415	0.282	-0.171	0.105
EOU4	0.331	**0.924**	0.134	0.583	0.138	0.492	0.102	0.41	0.515	0.613	0.543	0.345	-0.163	0.002
ESI1	0.448	0.178	**0.888**	0.288	0.643	0.103	0.335	0.474	0.175	0.361	0.271	0.222	0.041	0.705
ESI2	0.195	0.090	**0.800**	0.127	0.533	-0.039	0.187	0.32	-0.015	0.184	0.08	0.085	0.209	0.651
ESI3	0.370	0.081	**0.807**	0.305	0.569	0.167	0.184	0.362	0.293	0.262	0.312	0.337	0.085	0.445
FC1	0.575	0.462	0.261	**0.700**	0.440	0.589	0.12	0.304	0.466	0.45	0.537	0.535	-0.213	0.287
FC2	0.335	0.510	0.111	**0.804**	0.072	0.387	0.182	0.44	0.554	0.521	0.458	0.429	-0.014	-0.014
FC3	0.060	0.390	0.244	**0.630**	0.101	0.276	0.288	0.498	0.489	0.482	0.314	0.225	0.149	-0.007
FC4	0.202	0.395	0.313	**0.846**	0.401	0.428	0.37	0.451	0.419	0.472	0.363	0.353	0.166	0.324
ISI1	0.496	0.170	0.696	0.313	**0.941**	0.163	0.177	0.362	0.154	0.263	0.257	0.354	-0.067	**0.775**
ISI2	0.518	0.117	0.618	0.377	**0.936**	0.254	0.167	0.311	0.175	0.208	0.309	0.353	-0.058	**0.777**
ISI3	0.318	0.046	0.628	0.278	**0.872**	0.199	0.215	0.285	0.046	0.142	0.159	0.226	-0.038	**0.789**
RA1	0.393	0.302	-0.036	0.477	0.074	**0.870**	0.166	0.199	0.507	0.392	0.408	0.412	-0.337	-0.060
RA2	0.421	0.291	0.063	0.507	0.219	**0.839**	0.156	0.272	0.447	0.393	0.389	0.498	-0.189	0.077
RA3	0.469	0.548	0.164	0.585	0.194	**0.866**	0.231	0.502	0.625	0.704	0.627	0.564	-0.186	0.074
RA4	0.348	0.331	0.152	0.443	0.279	**0.889**	0.169	0.358	0.433	0.403	0.535	0.423	-0.218	0.185
TR1	-0.042	0.048	0.185	0.089	0.106	-0.011	**0.793**	0.096	0.116	0.12	0.146	-0.053	0.424	0.095
TR2	0.23	0.209	0.291	0.366	0.213	0.312	**0.970**	0.405	0.421	0.402	0.338	0.118	0.223	0.197
TR3	-0.039	-0.046	0.205	0.019	0.087	-0.124	**0.641**	0.145	0.036	0.027	-0.03	-0.16	0.506	0.185

TSPB1	0.346	0.309	0.329	0.492	0.227	0.284	0.287	**0.867**	0.672	0.558	0.35	0.419	-0.061	0.133
TSPB2	0.409	0.367	0.452	0.552	0.407	0.507	0.386	**0.885**	0.626	0.735	0.527	0.501	0.067	0.286
TSPB3	0.275	0.319	0.456	0.391	0.265	0.238	0.23	**0.892**	0.554	0.659	0.371	0.424	0.071	0.28
TSPC1	0.474	0.484	0.175	0.578	0.138	0.507	0.304	0.585	**0.916**	0.698	0.7	0.575	-0.046	0.023
TSPC2	0.441	0.366	0.282	0.622	0.266	0.566	0.341	0.689	**0.920**	0.658	0.654	0.692	-0.104	0.146
TSPC3	0.223	0.538	0.08	0.524	-0.027	0.509	0.284	0.591	**0.827**	0.678	0.551	0.515	-0.055	-0.132
TSPI1	0.387	0.559	0.249	0.544	0.152	0.56	0.321	0.621	0.704	**0.891**	0.651	0.563	-0.096	0.021
TSPI2	0.379	0.531	0.353	0.573	0.192	0.393	0.246	0.791	0.709	**0.877**	0.6	0.609	-0.003	0.09
TSPI3	0.359	0.519	0.249	0.525	0.260	0.526	0.29	0.463	0.511	**0.782**	0.538	0.447	0.089	0.102
TTF1	0.376	0.608	0.241	0.497	0.222	0.602	0.254	0.521	0.679	0.706	**0.914**	0.659	-0.089	0.079
TTF2	0.142	0.576	0.173	0.467	0.101	0.411	0.253	0.388	0.576	0.633	**0.863**	0.458	0.04	0.035
TTF3	0.475	0.473	0.326	0.570	0.373	0.498	0.238	0.357	0.63	0.52	**0.866**	0.632	-0.093	0.249
TTR1	0.356	0.413	0.170	0.463	0.126	0.470	-0.006	0.505	0.645	0.608	0.559	**0.859**	-0.225	-0.028
TTR2	0.382	0.257	0.324	0.437	0.398	0.395	-0.043	0.452	0.529	0.511	0.567	**0.862**	-0.206	0.249
TTR3	0.488	0.298	0.225	0.515	0.373	0.569	0.163	0.392	0.575	0.55	0.624	**0.880**	-0.165	0.274
MXU1	-0.275	-0.17	0.103	-0.152	-0.094	-0.300	0.209	0.013	-0.116	-0.04	-0.122	-0.295	**0.846**	0.038
MXU2	-0.232	-0.095	0.097	-0.021	-0.039	-0.074	0.194	-0.025	-0.063	-0.004	0.019	-0.089	**0.800**	0.094
MXU3	-0.279	0.119	-0.043	0.193	-0.031	-0.128	0.304	0.003	-0.022	0.046	0.095	-0.028	**0.671**	0.076
MXU4	-0.103	-0.075	0.196	0.045	-0.003	-0.256	0.397	0.122	-0.01	-0.01	-0.132	-0.218	**0.835**	0.158
VS1	0.34	-0.005	0.641	0.213	**0.734**	0.107	0.295	0.152	0.012	0.008	0.145	0.179	0.062	**0.890**
VS2	0.488	0.196	0.675	0.282	**0.828**	0.225	0.217	0.288	0.139	0.232	0.292	0.237	0.025	**0.908**
VS3	0.166	-0.179	0.562	0.051	**0.645**	-0.130	0.046	0.237	-0.123	-0.082	-0.082	0.099	0.196	**0.841**

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MXU= mHealth Use Anxiety.

5.3 Main Survey Preliminary Analysis: Data Cleaning and Screening

5.3.1 Missing Data

Missing data is one of the common issues in survey designs that contain self-reported measures (Scheffer, 2002). Missing data usually occurs when a respondent fails to provide responses to one or more of the items under observation (Allison, 2001). In social science research, missing data can lead to statistical issues such as parameter estimation bias and weak prediction power (Roth, 1994). When faced with missing data, it is important to determine the pattern of their occurrence; for example, whether they occur in a random or non-random manner (Little and Rubin, 2019). Unlike random missing data, in which values are missed randomly by respondents, non-random missing data can pose a generalizability issue due to the increased levels of bias in parameter estimations (Tabachinck and Fidell, 2007).

Given that the research data was collected online using the Qualtrics platform, the settings in Qualtrics have allowed the researcher to control the flow of questions displayed to respondents. To avoid the issue of missing data in the collected data set of Saudi Arabia and the United Kingdom samples, the researcher has designed the online questionnaire to allow respondents to proceed with the rest of the questionnaire questions only when they have provided responses to the previous ones. Therefore, no missing data has been found in the Saudi Arabian or United Kingdom samples.

5.3.2 Multivariate Outliers

According to Tabackinck and Fidell (2007), an outlier is "a case with such an extreme value on one variable (a univariate outlier) or such a strange combination of scores on one or more variables (a multivariate outlier)" (p. 106). On the other hand, Kline (2013) and Hair et al. (2006) have described outliers as cases that distinctively differ from other cases in the dataset. In spite of these different definitions, researchers generally agree that when using PLS-SEM, multivariate outliers should be detected and removed from the research dataset as they can significantly bias the parameter estimation employed by the ordinary least squares regression analysis implemented within PLS-SEM (Sarstedt and Mooi, 2019; Sarstedt et al., 2022). In fact, Field (2013) further argued that in PLS-SEM, multivariate outliers do not only cause a parameter estimation bias, but they can also cause an inference bias as their influence usually exceeds to influence the errors associated with those estimated parameters, which in turn can affect the conclusions derived from the hypothesized relationships among latent variables.

Mahalanobis distance technique is one of the widely used methods for detecting multivariate outliers in social science research (Kline, 2005; Tabachnick and Fidel, 2001). Its popularity as an outlier inspection method stems from its robustness performance that takes into consideration the shape of the dataset when identifying divergent cases. According to Tabachnick and Fidel (2001), a Mahalanobis distance is used to measure "the distance of a case from the centroid of the remaining cases where the centroid is the point created at the intersection of the means of all the variables" (p. 108). A Mahalanobis distance D^2 can be evaluated using a χ^2 distribution value with the degrees of freedom (df) equal to the number of variables (predictors) with a probability of $p < 0.001$. A χ^2 value with a $p < 0.001$ is considered to be an outlier according to Tabachnick and Fidel (2001).

In this research, the Mahalanobis distance technique was employed using SPSS version 23. In the dataset for Saudi Arabia and the United Kingdom, there are 47 variables at the scale measurement. These 47 variables are MXU1, MXU2, MXU3, MXU4, TR1, TR2, TR3, FC1, FC2, FC3, FC4, PEOU1, EOU2, EOU3, EOU4, RA1, RA2, RA3, RA4, VS1, VS2, VS3, VS4, ESI1, ESI2, ESI3, ISI1, ISI2, ISI3, TTR1, TTR2, TTR3, TTF1, TTF2, TTF3, TSPC1, TSPC2, TSPB1, TSPB2, TSPB3, TSPI1, TSPI2, TSPI3, AC1, AC2, AC3. The main goal is to detect multivariate outliers statistically by looking for unusual combinations of these variables for each respondent/case (χ^2 value with a $p < 0.001$). Once cases with multivariate outliers had been detected, they were removed from the datasets of both countries. For the Saudi Arabia dataset, 41 cases have been identified as multivariate outliers. The 41 cases are: 8, 16, 28, 53, 56, 62, 69, 75, 84, 90, 119, 152, 163, 165, 171, 204, 206, 207, 215, 223, 227, 245, 247, 248, 270, 279, 291, 321, 326, 229, 333, 349, 368, 385, 388, 394, 408, 413, 416, and 424. As for the United Kingdom's dataset, there are 46 cases that have been identified as multivariate outliers. These 46 cases are: 9, 19, 29, 37, 46, 62, 72, 113, 126, 142, 159, 179, 224, 228, 248, 253, 262, 273, 292, 296, 297, 307, 324, 330, 341, 360, 367, 380, 386, 401, 406, 416, 426, 436, 436, 436, 475, 488, 504, 511, 514, 518, 531, 532, 540, and 541. After removing multivariate outliers' cases, a total of 385 and 507 cases for Saudi Arabia and the United Kingdom, respectively, were used for further analysis.

5.3.3 Multivariate Normality

One of the important early steps in multivariate analysis is to assess the shape of the collected data by examining the distribution of the scores around the central mean (Tabachinck and Fidell, 2014; Hair et al., 2017). A normal distribution usually takes a bull-shape symmetrical curve with the greatest frequency of scores located in the middle and smaller frequencies toward the end of the extreme (Pallant, 2020).

Multivariate normality can be assessed either graphically or statistically. Graphically, multivariate normality can be visually assessed by checking the shape of the distributed data using histograms or P–P plot (probability–probability plot) tests. These two tests compare the observed data values with a distribution approximating the normal distribution. If the observed data distribution largely follows the diagonal lines, then the distribution is considered normal (Hair et al., 2006). Statistically, multivariate normality can be assessed using skewness and kurtosis values (Tabachinck and Fidell, 2014). According to Pallant (2020), "the skewness value provides an indication of the symmetry of the distribution. Kurtosis, on the other hand, provides information about the peakedness of the distribution" (p. 57). The recommended values of skewness and kurtosis by Hair et al. (2010) and Bryne (2010) are between – 2 and + 2 for skewness and between –7 and +7 for kurtosis, respectively. According to Hair et al. (2017), distributions that exhibit skewness and/or kurtosis beyond the recommended values are deemed nonnormal. As shown in Table 5.7, the results show that for the SA and UK sample variables, variables were normally distributed. However, given that skewness and kurtosis values are sensitive to the sample size, Tabachinck and Fidell (2014) recommend the use of graphical methods to visually verify the shape of independent variables distributions, especially as the values of skewness and kurtosis become weaker with larger sample sizes (Hair et al., 2017; Tabachinck and Fidell, 2014). Therefore, a visual detection of data normality using histograms and the P–P plot was performed, and the results showed acceptable levels of variables distribution normality.

Table 5.7 Multivariate Normality Results

Construct	Saudi Arabia				United Kingdoms			
	Mean	**Std. Deviation**	**Skewness**	**Kurtosis**	**Mean**	**Std. Deviation**	**Skewness**	**Kurtosis**
MUX1	3.5610	1.78449	0.378	-0.876	4.4359	1.61555	-0.152	-1.115
MUX1	4.1740	1.90896	-0.171	-1.346	3.9428	1.72137	0.044	-1.198
MUX1	3.9429	1.99266	-0.026	-1.372	3.2071	1.64140	0.575	-0.592
MUX1	4.0442	1.79427	-0.028	-1.159	3.9310	1.62283	0.143	-0.969
TR1	2.0857	1.20348	1.628	2.826	2.4517	1.04216	0.918	1.311
TR2	1.9896	1.03828	1.635	3.693	2.6588	1.09794	0.752	0.776
TR3	2.4727	1.56289	1.061	0.281	2.8757	1.39676	0.607	-0.131
FC1	2.3351	1.16567	1.147	1.651	3.0651	1.18859	0.250	-0.148
FC2	2.0468	1.07669	1.165	1.465	2.6371	1.13272	0.419	-0.112
FC2	1.8831	0.89521	1.326	2.519	2.4398	1.04533	0.671	0.490
FC4	2.3065	1.23726	1.258	1.461	2.8698	1.15875	0.554	0.382
EOU1	1.7870	0.81095	1.115	1.294	2.1124	1.05444	1.236	1.961
EOU2	1.7325	0.81241	1.259	1.944	2.1795	1.09857	1.175	2.096
EOU3	2.1584	1.36486	1.719	2.796	2.7692	1.38456	0.850	0.264
EOU4	2.0260	1.06768	1.316	2.132	2.4359	1.03560	0.788	1.031

RA1	2.8961	1.71835	0.663	-0.609	2.8363	1.42355	0.658	-0.084
RA2	2.2260	1.23885	1.133	1.095	2.5819	1.15529	0.718	0.675
RA3	2.5117	1.37329	0.782	-0.081	3.0888	1.29990	0.328	-0.509
RA4	2.6182	1.52486	0.888	0.050	2.8797	1.40134	0.583	-0.232
VS1	3.3792	1.81762	0.485	-0.880	4.7830	1.66701	-0.370	-0.909
VS2	3.2727	1.68662	0.587	-0.612	4.7436	1.66969	-0.264	-1.126
VS3	3.2000	1.67984	0.596	-0.537	5.0079	1.56036	-0.392	-0.785
VS4	3.9818	1.89082	0.059	-1.193	5.1578	1.48735	-0.370	-0.774
ESI1	3.0571	1.73711	0.724	-0.422	4.8304	1.53188	-0.256	-0.957
ESI2	3.2883	1.70095	0.536	-0.668	4.9270	1.51168	-0.362	-0.779
ESI3	2.9351	1.49946	0.750	-0.009	4.0099	1.44254	0.419	-0.715
ISI1	2.8130	1.42936	0.741	0.005	4.2071	1.43451	0.213	-0.308
ISI2	2.9714	1.51441	0.636	-0.205	4.3905	1.45055	0.121	-0.363
ISI3	2.9091	1.55441	0.805	0.036	4.8501	1.51188	-0.089	-0.884
TTI	2.3117	1.16882	1.065	1.152	3.0414	1.11594	0.561	0.690
TTI2	2.9039	1.37637	0.463	-0.243	4.0434	1.09891	0.084	0.349
TTI3	2.6623	1.35986	0.829	0.072	3.3925	1.10236	0.403	0.391
TTF1	2.0649	1.00179	1.104	1.618	2.6016	1.02491	0.714	1.119
TTF2	1.9377	0.96892	1.161	1.725	2.8304	1.04201	0.638	0.842

TTF3	2.5273	1.24579	0.791	0.332	3.1124	1.16146	0.555	0.604
TSPC1	2.2727	1.12310	0.756	0.156	3.0256	1.09857	0.578	0.663
TSPC2	2.3247	1.16415	0.947	0.885	3.1420	1.13494	0.476	0.439
TSPC3	2.2286	1.07273	0.896	0.564	3.0039	1.24633	0.521	0.332
TSPB1	2.3299	1.17826	0.921	0.505	3.4339	1.33258	0.230	-0.263
TSPB2	2.3065	1.21389	1.037	0.922	3.0375	1.13539	0.536	0.737
TSPB3	2.6130	1.44998	0.794	0.058	3.5917	1.45178	0.148	-0.534
TSPI1	2.3143	1.16477	0.798	0.323	2.3511	1.10112	0.814	0.978
TSPI2	2.4935	1.30128	0.716	0.084	2.2564	1.12523	0.995	1.396
TSPI3	2.2545	1.13314	0.837	0.376	2.0828	1.12861	1.178	1.630
AC1	2.1818	1.15388	1.163	1.324	3.9191	1.50210	0.310	-0.515
AC2	2.2208	1.12063	1.018	0.974	3.5582	1.53422	0.551	-0.405
AC3	2.4182	1.29469	0.836	0.132	3.6824	1.56914	0.387	-0.498

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

5.3.4 Multicollinearity Test

Multicollinearity occurs when there is a high correlation among independent variables (Hair et al., 2017). Multicollinearity among independent variables can be assessed using variance inflation factor (VIF) and tolerance values. Kilne (2015) and Premkumar et al. (2008) indicate that multicollinearity becomes a problem when VIF values are more than 10 and tolerance values are less than 0.1. As shown in Tables 5.8, 5.9, 5.10, and 5.11, all VIF and tolerance values for the dependent variables trust in mHealth service provider, trust in mHealth service, mHealth use anxiety, and mHealth acceptance were within the acceptable values range, indicating that multicollinearity is not a problem in SA and UK samples. In addition to VIF and tolerance values, Hair et al. (2010) indicate that if the correlation coefficient among independent variables is lower than 0.9, this indicates that multicollinearity is not a problem. As shown in Tables 5.8, 5.9, 5.10, and 5.11, all correlation coefficients are less than the recommended value, which indicates there is no multicollinearity problem in both SA and UK samples.

Table 5.8. Multicollinearity Results for Trust in mHealth Service Provider

Construct	SA					UK				
	β	t-Value	Sig.	Tolerance	VIF	β	t-Value	Sig.	Tolerance	VIF
ESI	0.155	3.003	0.003	0.551	1.815	0.185	4.383	0.000	0.708	1.412
FC	0.235	5.562	0.000	0.817	1.223	0.271	7.232	0.000	0.891	1.122
RA	0.395	8.693	0.000	0.711	1.406	0.405	10.722	0.000	0.881	1.134
VS	0.095	1.785	0.075	0.522	1.915	0.027	0.646	0.519	0.706	1.416

Note: FC= Facilitating Conditions; ESI= External Social Influence; RA= Relative Advantage; VS= Visibility

Table 5.9 Multicollinearity Results for Trust in mHealth Service										
Construct	**SA**					**UK**				
	β	**t-Value**	**Sig.**	**Tolerance**	**VIF**	**β**	**t-Value**	**Sig.**	**Tolerance**	**VIF**
ISI	0.279	7.498	0.000	0.662	1.511	0.076	2.658	0.008	0.917	1.091
EOU	0.122	3.487	0.001	0.755	1.325	0.080	2.520	0.012	0.742	1.347
RA	0.174	4.318	0.000	0.566	1.767	0.254	7.609	0.000	0.671	1.491
TSP	0.432	10.428	0.000	0.535	1.870	0.564	16.715	0.000	0.656	1.524

Note: EOU= Ease of Use; RA= Relative Advantage; ISI= Interpersonal Social Influence; TSP= Trust in Service Provider

Table 5.10 Multicollinearity Results for mHealth Use Anxiety

Construct	**SA**					**UK**				
	β	**T-Value**	**Sig.**	**Tolerance**	**VIF**	**β**	**t-Value**	**Sig.**	**Tolerance**	**VIF**
TR	0.449	9.316	0.000	0.905	1.105	0.360	8.957	0.000	0.910	1.098
TT	-0.110	-2.144	0.033	0.798	1.252	-0.311	-7.325	0.000	0.818	1.222
EOU	-0.193	-3.682	0.000	0.765	1.307	-0.232	-5.275	0.000	0.762	1.312

Note: TT= Trust in mHealth Service; EOU= Ease of Use; TR= Trialability

Table 5.11. Multicollinearity Results for mHealth Acceptance

Construct	**SA**					**UK**				
	β	**t-Value**	**Sig.**	**Tolerance**	**VIF**	**β**	**t-Value**	**Sig.**	**Tolerance**	**VIF**
MUX	-0.074	-2.215	0.027	0.959	1.042	-0.272	-7.444	0.000	0.869	1.151
VS	0.127	3.358	0.001	0.752	1.330	0.228	6.564	0.000	0.958	1.044
TT	0.322	6.606	0.000	0.449	2.227	0.245	4.650	0.000	0.416	2.403
TSP	0.422	8.413	0.000	0.425	2.354	0.202	3.946	0.000	0.440	2.270

Note: TSP= Trust in Service Provider; TT= Trust in mHealth Service; VS= Visibility; MUX= mHealth Use Anxiety.

5.3.5 Demographic Frequency Profile

From the 1st of June to the 31st of July 2021, a total of 427 completed responses in Saudi Arabia (SA) and 553 responses in the United Kingdom (UK) have been received from research participants. After removing problematic responses (e.g., outliers), a total of 385 responses in Saudi Arabia and 507 responses in the United Kingdom were used for testing the research proposed model. As shown in Table 5.12, 38.4% of Saudi respondents were male and 61.6% were female within the age groups of 18–24 (20.0%), 25–34 (31.9%), 35–44 (27.3%), 45–54 (14.5%), 55–64 (5.5%), and ≥ 65 (0.8%). On the other hand, 30.0% of UK respondents were male and 70.0% were female within the age groups of 18–24 (18.9%), 25–34 (32.9%), 35–44 (25.4%), 45–54 (11.0%), 55–64 (9.1%), and ≥ 65 (2.6%).

Furthermore, as shown in Table 5.12, the majority of SA and UK respondents held a bachelor's degree (49.1% in SA and 40.8% in UK), followed by high school graduates (16.6% in SA and 27.8% in UK), master's degrees (14.5% in SA and 15.2% in UK), and diploma degrees (10.1% in SA and 11.2% in UK). The rest of respondents were doctorate degree holders (4.2% in SA and 1.4% in UK), professional degree holders (0.3% in Saudi and 2.0% in UK), and less than high graduate degree holders (5.2% in Saudi and 1.6 in UK). Respondents' income ranged from high income to low income as follows: ≥ 23,000 (5.7% in SA and 1.0% in UK), 19,000-22,999 (4.5% in SA and 4.5% in UK), 15,000-18,999 (9.8% in SA and 1.8% in UK), 11,000-14,999 (14.1% in SA and 2.4% in UK), 7,000-10,999 (14.9% in SA and 1.0% in UK), 3,000-6,999 (15.2% in SA and 7.6% in UK), < 3000 (36.2% in SA and 72.0% in UK).

Table 5.12 Research Participants Demographic Profile

Demographic Profile	Saudi Arabia		United Kingdom	
	Number	Percentage	Number	Percentage
Gender				
Male	148	38.4	152	30.0
Female	237	61.6	355	70.0
Total	385		507	
Age				
18-24	77	20.0	96	18.9
25-34	123	31.9	167	32.9
35-44	105	27.3	129	25.4
45-54	56	14.5	56	11.0
55-64	21	5.5	46	9.1
≥ 65	3	0.8	13	2.6
Education				
Less Than High School	20	5.2	8	1.6
High School Graduate	64	16.6	141	27.8
Diploma Degree	39	10.1	57	11.2
Bachelor's degree	189	49.1	207	40.8
Master's degree	56	14.5	77	15.2
Professional Degree	1	0.3	10	2.0
Doctorate Degree	16	4.2	7	1.4
Income				
< 3000	143	36.2	365	72.0
3,000-6,999	57	15.2	40	7.9
7,000-10,999	57	14.9	5	1.0
11,000-14,999	53	14.1	12	2.4
15,000-18,999	36	9.8	9	1.8
19,000-22,999	17	4.5	23	4.5
≥ 23,000	22	5.7	53	10.2

5.3.6 Non-Response Bias

Non-response bias is another issue accompanying survey research. It usually occurs when there is a significant difference between research respondents and non-respondents, which may affect the representation nature of the obtained sample to the entire population (Ghauri and Gronhaug, 2010; Wallace and Sheetz, 2014).

With the absence of a sampling frame, it was not possible to compare non-responders to responders. Instead, this research has compared the 40 early responders to the 40 late responders received in the data collection phase, assuming that late responders are much like non-responders, as suggested by Miller and Smith (1983) and Wallace and Sheetz (2014). Such an assumption is built on the basis that "people who failed to fill out the questionnaire were more like those who delayed their responses than those who answered right away", as suggested by Babbie (1990, p. 180). Accordingly, each respondent was categorized according to the date and time of their response in order to distinguish between early and late responders (Wallace and Sheetz, 2014). The first and last 40 respondents were then compared in terms of their demographical variables: age, gender, education, and income. And the responses in between were deleted to establish the separation between early and late respondents.

To assess non-response bias, analysis of variance (ANOVA) was used to compare the mean value of each demographical variable from early responders to that of late responders, as shown in Table 5.13. The results of the ANOVA test suggest that there were no significant differences between the early and late respondents in both the SA and UK samples, which means that respondents are not significantly different from the non-respondents. Consequently, non-response bias was not considered a serious limitation in this study.

Table 5. 13 ANOVA Test Results

Demographical variable	SA		UK	
	ANOVA		ANOVA	
	F	Sig.	F	Sig
Gender	0.941	0.472	0.899	0.346
Age	1.224	0.304	0.226	0.636
Education	0.493	0.811	0.299	0.589
Income	0.348	0.909	0.063	0.803

5.3.5 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a structural equation modeling technique that seeks to verify the number of latent variables that account for the variation and covariation among a set of indicators in the collected dataset (Brown and Moore, 2012). According to Harrington (2009), the aim of CFA is to verify and confirm the measurement structure of latent variables by examining the correlation between a set of indicators and their corresponding latent variables (also known as factor loadings). This makes CFA an essential step in establishing the quality of the latent measurement scale before proceeding with the rest of the measurement analysis.

As indicated by Tabachnick and Fidell (2001), the minimum acceptable value for factor loadings in social science research is a value that is equal to or greater than 0.32, while loadings over 0.45 are considered fair, loadings over 0.55 are considered good, loadings over 0.63 are considered very good, and loadings over 0.71 are considered excellent. Given that factors loading equal to or greater than 60 can explain more than half of the variance in its corresponding construct, this research uses the value of 60 as its benchmark for factor loadings as recommended by Hair et al. (2017), which is a very good level of variance in social science research.

The CFA was conducted using SmartPLS software version 3.9.9. As shown in Tables 5.14 and 5.15, FC1 and FC2 from the Saudi Arabia measurement model and ESI3 and TR3 from the United Kingdom measurement model were lower than the suggested benchmark of 60. Accordingly, these items were removed from their measurement models to improve the quality of the measurement scale of their latent variables. Hence, FC1 and FC2 were removed from the Saudi Arabia measurement model, while ESI3 and TR3 were removed from the United Kingdom measurement model to improve the measurement models' validity and reliability.

Table 5.14 Confirmatory Factor Analysis for SA

Item	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC1	0.933										
AC2	0.938										
AC3	0.934										
ESI1		0.905									
ESI2		0.910									
ESI3		0.751									
FC1			0.581								
FC2			0.819								
FC3			0.836								
FC4			0.558								
ISI1				0.911							
ISI2				0.935							
ISI3				0.881							
MUX1					0.777						
MUX2					0.856						
MUX3					0.842						
MUX4					0.828						
EOU1						0.781					
EOU2						0.781					
EOU3						0.654					
EOU4						0.823					
RA1							0.825				
RA2							0.860				
RA3							0.885				
RA4							0.799				
TR1								0.791			
TR2								0.819			
TR3								0.746			
TSPB1									0.846		
TSPB2									0.815		
TSPB3									0.778		
TSPC1									0.789		
TSPC2									0.853		
TSPC3									0.849		
TSPI1									0.834		
TSPI2									0.748		
TSPI3									0.809		
TTF1										0.771	
TTF2										0.716	
TTF3										0.853	

TTR1	0.864	
TTR2	0.779	
TTR3	0.857	
VS1		0.846
VS2		0.864
VS3		0.875
VS4		0.859

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

Table 5.15 Confirmatory Factor Analysis for UK

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC1	0.948										
AC2	0.950										
AC3	0.939										
ESI1		0.914									
ESI2		0.934									
ESI3		0.490									
FC1			0.668								
FC2			0.845								
FC3			0.804								
FC4			0.778								
ISI1				0.837							
ISI2				0.904							
ISI3				0.902							
TX1					0.753						
TX2					0.866						
TX3					0.775						
TX4					0.827						
EOU1						0.846					
EOU2						0.884					
EOU3						0.614					
EOU4						0.870					
RA1							0.855				
RA2							0.862				
RA3							0.848				
RA4							0.844				
TR1								0.881			
TR2								0.839			
TR3								0.559			
TSPB1									0.798		
TSPB2									0.797		
TSPB3									0.715		
TSPC1									0.788		
TSPC2									0.841		
TSPC3									0.844		
TSPI1									0.760		
TSPI2									0.660		
TSPI3									0.656		
TTF1										0.804	
TTF2										0.850	
TTF3										0.826	

TTR1	0.811	
TTR2	0.629	
TTR3	0.816	
VS1		0.911
VS2		0.904
VS3		0.853
VS4		0.868

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

5.4 Main Survey Data Analysis: Measurement and Structural Models

After verifying the measurement scale structure of the proposed latent variables, the next step was to validate the quality of the measurement model. Following Hair et al.'s (2017) recommendation, a two-step approach was adopted to analyze the proposed research model. The first step was primarily concerned with the establishment of the validity and reliability of the reflective measurement model, while the second step was concerned with the validation of proposed causal relationships in the structural model. The analysis of the research model was carried out using SmartPLS version 3.9.9.

5.4.1 Reflective Measurement Model

When using reflective models, it is important to first examine the quality of the latent variables in terms of their reliability and validity. In reflective modelling, each construct is measured by a set of indicators that share a common theme. These indicators are thus assumed to be theoretically interchangeable (Jarvis et al., 2003; Urbach et al., 2010; Churchill, 1979; Nunnally and Bernstein, 1994). This means that the removal or inclusion of one or more of these indicators from the construct domain will not affect the content validity of that construct since each indicator can equally represent its underlying construct without affecting the rest of the indicators.

Given that these measures are conceptually interchangeable, they should therefore also be highly correlated (Christophersen and Konradt, 2012; Haenlein and Kaplan, 2004; Hair et al., 2017).

High correlations among indicators are interpreted as an indication of high internal consistency; in other words, they are an indicator of high construct reliability (Bollen, 1984).

According to Hair et al. (2017), reliability is a necessary condition for construct validity (Hair et al., 2017). In social science research, validity is often assessed in terms of construct convergent and discriminant validity. Convergent validity is used to examine the degree to which each indicator of a given latent variable correlates positively with other indicators of the same construct, while discriminant validity is used to test the extent to which each construct in the proposed research model is significantly distinct from other constructs by empirical standards (Hair et al., 2017).

5.4.1.1 Reflective Measurement Model Reliability

Cronbach's alpha and composite reliability measures are the two frequently used tests to assess the reliability of a given construct. Cronbach's alpha value that is equal to or greater than 0.70 is the recommended value in social science research for a satisfactory construct reliability (Nunnally and Bernstein, 1994). As shown in Table 5.16, all Cronbach's alpha values in the United Kingdom Sample and Saudi Arabia sample exceeded the recommended value of 0.70, except for the construct of Trialability in the Saudi Arabia sample. Although the Cronbach's alpha value of trialability (0.693) was lower than the recommended benchmark, it surpassed the generally accepted reliability threshold value of 0.60, which is considered as an acceptable index of internal construct consistency in social science research (Nunnally and Bernstein, 1994; Pallant, 2001; Kim et al., 2009).

In addition to Cronbach's alpha values, reliability was measured using composite reliability. According to Hair et al. (2017), composite reliability values can vary between 0 and 1. The suggested threshold for composite reliability is a value that is equal to or greater than 0.70 (Hair et al. 2009; Nunnally and Bernstein, 1994). As shown in Table 5.16, all composite reliability values for Saudi Arabia and the United Kingdom samples were greater than the recommended value, thereby, indicating a good level of constructs reliability.

Table 5.16 Reflective Measurement Model Reliability

	Cronbach's Alpha		Composite Reliability	
	Saudi Arabia	The United Kingdom	Saudi Arabia	The United Kingdom
mHealth Acceptance	0.928	0.941	0.954	0.962
External Social Influence	0.818	0.889	0.893	0.947
Facilitating Conditions	0.765	0.777	0.893	0.858
Interpersonal Social Influence	0.896	0.856	0.935	0.912
mHealth Use Anxiety	0.845	0.821	0.896	0.881
Ease of Use	0.759	0.825	0.846	0.883
Relative Advantage	0.863	0.875	0.907	0.914
Trialability	0.693	0.758	0.829	0.892
Trust in mHealth Service Provider	0.936	0.901	0.946	0.920
Trust in mHealth	0.893	0.880	0.919	0.910
Visibility	0.884	0.907	0.920	0.935

5.4.1.2 Reflective Measurement Model Validity

5.4.1.2.1 Convergent Validity

Constructs were measured in terms of their convergent and discriminant validity. In terms of convergent validity, Fornell and Larcker (1981) recommend the use of Average Variance Extracted (AVE) as a criterion for assessing the interrelations among a set of indicators of a given latent variable. An AVE value that is equal to or greater than 0.5 is an indicator of sufficient convergent validity, which means that the latent variable is able to explain more than half of the variance of its indicators on average (Tabachnick and Fidell, 2000; Hair et al., 2017). As shown in Table 5.17, all AVE values of Saudi Arabia and United Kingdom samples were above the recommended value of “0.5”. Thus, indicating a satisfactory level of convergent validity.

Table 5.17 Convergent Validity

	Saudi Arabia	United Kingdom
mHealth Acceptance	0.874	0.894
External Social Influence	0.738	0.900
Facilitating Conditions	0.807	0.604
Interpersonal Social Influence	0.827	0.777
mHealth Use Anxiety	0.683	0.650
Ease of Use	0.581	0.658
Relative Advantage	0.710	0.727
Trialability	0.618	0.805
Trust in mHealth Service Provider	0.663	0.591
Trust in mHealth	0.654	0.628
Visibility	0.742	0.782
mHealth Acceptance	0.874	0.894
External Social Influence	0.738	0.900

5.4.1.2.2 Discriminant Validity

Discriminant validity, on the other hand, was assessed in terms of indicators cross loadings and Fornell-Larcker criterion as recommended by Hair et al. (2017) and Chin (1998). To establish discriminant validity in terms of cross loadings, each indicator outer loading on its hypothesized construct should be greater than any of its outer cross-loadings on other constructs (Chin, 1998; Al-Emran et al., 2019). As shown on Tables 5.18 and 5.19, in Saudi Arabia sample, all factor loadings, which are marked in bold, were greater than their corresponding cross loadings, thus, representing a good level of discriminant validity. However, in the United Kingdom sample, TSPC1 had high cross loadings on the factors of trust in mHealth service provider (0.788) and trust in mHealth service (0.720). To restore discriminant validity, Hair et al. (2017) suggests removing all indicators with high cross-loadings from the proposed measurement model. Therefore, TSPC1 was removed from the United Kingdom measurement model to re-establish trust in mHealth service provider discriminant validity.

In addition to cross-loadings, Fornell-Larcker criterion suggests that each construct's AVE should be greater than its squared correlation with any other construct to establish sufficient levels of discriminant validity (Fornell and Larcker, 1981). As shown in Tables 5.9 and 5.10, the diagonal elements are greater than the corresponding off-diagonal elements, illustrating that the square root of each construct's AVE was greater than the correlation of the construct to other latent variables. Thereby, meeting the requirements of adequate discriminant validity in both samples.

Table 5.18 Discriminant Validity-Cross Loadings for SA

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC1	0.933	0.374	0.366	0.535	-0.112	0.412	0.558	0.2	0.645	0.713	0.421
AC2	0.938	0.351	0.369	0.519	-0.092	0.401	0.525	0.173	0.651	0.671	0.406
AC3	0.934	0.325	0.325	0.519	-0.129	0.338	0.485	0.163	0.644	0.657	0.427
ESI1	0.351	0.905	0.127	0.622	0.131	0.149	0.302	0.091	0.366	0.361	0.619
ESI2	0.286	0.910	0.103	0.624	0.153	0.128	0.253	0.099	0.316	0.32	0.613
ESI3	0.329	0.751	0.188	0.55	0.23	0.143	0.38	0.163	0.378	0.394	0.473
FC2	0.323	0.164	0.869	0.231	0.043	0.344	0.338	0.246	0.375	0.362	0.196
FC3	0.355	0.128	0.927	0.194	-0.029	0.561	0.326	0.304	0.375	0.418	0.133
ISI1	0.537	0.616	0.277	0.911	-0.002	0.241	0.441	0.091	0.525	0.579	0.67
ISI2	0.547	0.673	0.205	0.935	0.072	0.211	0.479	0.112	0.523	0.601	0.688
ISI3	0.44	0.617	0.148	0.881	0.068	0.153	0.371	0.086	0.433	0.501	0.631
EOU1	0.292	0.161	0.434	0.181	-0.097	0.798	0.292	0.181	0.346	0.395	0.109
EOU2	0.258	0.08	0.422	0.116	-0.076	0.793	0.305	0.271	0.321	0.328	0.073
EOU3	0.257	0.085	0.303	0.114	-0.018	0.636	0.296	0.26	0.245	0.226	0.125
EOU4	0.428	0.154	0.406	0.246	-0.161	0.809	0.479	0.2	0.42	0.45	0.205
RA1	0.484	0.339	0.295	0.46	-0.018	0.384	0.825	0.142	0.48	0.526	0.396
RA2	0.439	0.272	0.281	0.354	-0.026	0.493	0.852	0.196	0.515	0.502	0.306
RA3	0.475	0.309	0.315	0.385	0.007	0.369	0.884	0.168	0.507	0.527	0.315
RA4	0.487	0.289	0.347	0.402	0.071	0.285	0.807	0.145	0.507	0.506	0.377
TR1	0.165	0.086	0.254	0.095	0.221	0.24	0.12	0.798	0.138	0.192	0.059
TR2	0.295	0.098	0.345	0.119	0.171	0.337	0.227	0.816	0.295	0.315	0.04
TR3	0.013	0.126	0.146	0.043	0.42	0.12	0.111	0.744	0.089	0.058	0.046
TSPB1	0.591	0.357	0.328	0.474	-0.07	0.367	0.566	0.199	0.846	0.652	0.381
TSPB2	0.53	0.32	0.294	0.44	-0.024	0.339	0.484	0.184	0.815	0.601	0.363
TSPB3	0.541	0.327	0.28	0.445	-0.022	0.238	0.417	0.107	0.777	0.54	0.362
TSPC1	0.542	0.352	0.356	0.47	-0.001	0.361	0.495	0.206	0.789	0.609	0.348
TSPC2	0.603	0.351	0.318	0.495	-0.033	0.423	0.578	0.23	0.853	0.66	0.372
TSPC3	0.579	0.318	0.421	0.424	-0.033	0.432	0.539	0.231	0.849	0.654	0.305
TSPI1	0.545	0.363	0.359	0.475	-0.074	0.339	0.448	0.173	0.834	0.582	0.357
TSPI2	0.528	0.329	0.286	0.378	-0.058	0.307	0.379	0.123	0.748	0.519	0.305
TSPI3	0.602	0.286	0.393	0.382	-0.096	0.436	0.434	0.119	0.809	0.58	0.286
TTF1	0.553	0.278	0.442	0.389	-0.045	0.419	0.424	0.24	0.526	0.771	0.25
TTF2	0.532	0.175	0.412	0.313	-0.131	0.494	0.312	0.218	0.513	0.716	0.145

TTF3	0.614	0.34	0.366	0.512	-0.079	0.391	0.555	0.218	0.668	0.853	0.42
TTR1	0.661	0.398	0.328	0.554	-0.123	0.38	0.545	0.168	0.631	0.864	0.413
TTR2	0.542	0.377	0.241	0.583	-0.045	0.298	0.485	0.129	0.604	0.779	0.486
TTR3	0.62	0.411	0.354	0.608	-0.071	0.339	0.608	0.165	0.629	0.857	0.436
MUX1	-0.035	0.177	-0.008	0.086	0.777	-0.111	0.01	0.291	-0.01	-0.009	0.144
MUX2	-0.106	0.212	0.011	0.092	0.856	-0.101	0.037	0.322	-0.032	-0.045	0.121
MUX3	-0.144	0.137	0.015	-0.02	0.842	-0.11	-0.02	0.271	-0.089	-0.14	0.044
MUX4	-0.101	0.121	-0.011	0.011	0.828	-0.095	0.005	0.295	-0.051	-0.136	0.057
VS1	0.352	0.515	0.100	0.542	0.102	0.153	0.335	0.037	0.328	0.349	0.846
VS2	0.38	0.581	0.179	0.619	0.059	0.151	0.437	0.053	0.386	0.381	0.864
VS3	0.389	0.594	0.222	0.72	0.077	0.162	0.34	0.066	0.356	0.439	0.875
VS4	0.415	0.597	0.102	0.619	0.139	0.119	0.313	0.053	0.374	0.383	0.859

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

Table 5.19 Discriminant Validity-Cross Loadings for UK

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC1	0.948	0.285	0.206	0.388	-0.438	0.253	0.38	0.159	0.468	0.497	0.326
AC2	0.950	0.254	0.248	0.371	-0.389	0.281	0.402	0.226	0.491	0.523	0.289
AC3	0.939	0.259	0.245	0.336	-0.393	0.285	0.396	0.218	0.471	0.506	0.273
ESI1	0.252	0.948	-0.013	0.511	-0.001	-0.041	0.051	-0.051	0.183	0.154	0.536
ESI2	0.283	0.949	0.000	0.523	0.029	-0.042	0.009	-0.057	0.165	0.127	0.543
FC1	0.353	0.113	0.658	0.111	-0.168	0.43	0.318	0.338	0.287	0.311	0.174
FC2	0.167	0.017	0.847	0.004	-0.026	0.457	0.263	0.396	0.324	0.258	-0.004
FC3	0.076	-0.110	0.810	-0.05	0.016	0.417	0.201	0.371	0.296	0.23	-0.111
FC4	0.175	-0.039	0.780	0.042	-0.048	0.422	0.252	0.39	0.342	0.296	0.018
ISI1	0.285	0.450	0.043	0.837	-0.131	0.013	0.127	-0.002	0.228	0.216	0.440
ISI2	0.362	0.470	0.043	0.904	-0.116	-0.008	0.174	0.056	0.239	0.25	0.468
ISI3	0.368	0.516	0.008	0.902	-0.100	-0.026	0.13	-0.018	0.198	0.207	0.574
EOU1	0.199	-0.086	0.56	-0.026	-0.200	0.846	0.371	0.396	0.355	0.343	-0.011
EOU2	0.257	-0.039	0.522	-0.023	-0.207	0.884	0.38	0.365	0.406	0.417	0.038
EOU3	0.122	0.015	0.227	0.007	-0.133	0.614	0.226	0.15	0.179	0.224	0.063
EOU4	0.321	-0.011	0.422	0.018	-0.325	0.87	0.49	0.273	0.412	0.454	0.076
RA1	0.352	-0.024	0.233	0.137	-0.299	0.397	0.856	0.186	0.39	0.494	0.027
RA2	0.339	-0.022	0.357	0.118	-0.210	0.471	0.859	0.277	0.477	0.545	0.062
RA3	0.373	0.064	0.284	0.147	-0.231	0.346	0.848	0.203	0.433	0.493	0.127
RA4	0.354	0.091	0.251	0.154	-0.192	0.368	0.846	0.232	0.444	0.504	0.138
TR1	0.103	-0.067	0.429	-0.013	0.136	0.278	0.154	0.900	0.159	0.156	-0.045
TR2	0.279	-0.036	0.437	0.036	-0.030	0.407	0.325	0.894	0.295	0.334	0.031
TSPB1	0.432	0.23	0.29	0.288	-0.242	0.287	0.402	0.082	0.815	0.573	0.263
TSPB2	0.404	0.137	0.306	0.202	-0.253	0.354	0.443	0.187	0.811	0.607	0.162
TSPB3	0.482	0.254	0.25	0.310	-0.23	0.22	0.355	0.078	0.734	0.507	0.248
TSPC2	0.483	0.162	0.33	0.237	-0.249	0.363	0.497	0.201	0.818	0.706	0.216
TSPC3	0.455	0.2	0.311	0.228	-0.246	0.34	0.463	0.165	0.835	0.672	0.185
TSPI1	0.292	0.045	0.345	0.099	-0.214	0.396	0.33	0.301	0.769	0.537	0.004
TSPI2	0.204	0.006	0.348	0.019	-0.152	0.379	0.327	0.318	0.677	0.427	-0.060
TSPI3	0.243	0.003	0.345	0.052	-0.158	0.385	0.272	0.317	0.672	0.452	-0.048
TTF1	0.387	0.057	0.377	0.124	-0.218	0.452	0.474	0.292	0.607	0.803	0.09
TTF2	0.396	0.051	0.32	0.152	-0.27	0.419	0.492	0.249	0.609	0.85	0.107
TTF3	0.452	0.142	0.275	0.216	-0.299	0.407	0.574	0.221	0.652	0.826	0.164
TTR1	0.509	0.17	0.292	0.292	-0.358	0.362	0.476	0.235	0.616	0.811	0.181
TTR2	0.333	0.16	0.091	0.231	-0.252	0.151	0.327	0.069	0.374	0.629	0.169

TTR3	0.457	0.13	0.281	0.193	-0.32	0.334	0.469	0.195	0.623	0.816	0.169
MUX1	-0.246	0.13	-0.074	-0.013	0.756	-0.274	-0.231	0.034	-0.24	-0.288	0.067
MUX2	-0.384	0.012	-0.078	-0.124	0.864	-0.231	-0.186	0.005	-0.219	-0.291	0.001
MUX3	-0.293	-0.057	0.016	-0.137	0.767	-0.129	-0.135	0.124	-0.159	-0.21	-0.053
MUX4	-0.432	-0.027	-0.079	-0.135	0.833	-0.241	-0.3	0.045	-0.294	-0.36	-0.047
MUX1	0.266	0.496	0.025	0.534	-0.022	0.071	0.12	0000	0.172	0.171	0.911
VS2	0.312	0.515	0.058	0.500	-0.056	0.100	0.127	0.016	0.183	0.206	0.904
VS3	0.278	0.45	0.008	0.461	0.009	0.019	0.045	0000	0.156	0.144	0.852
VS4	0.253	0.546	-0.013	0.503	0.027	-0.031	0.072	-0.045	0.128	0.128	0.868

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

Table 5.20 Discriminant Validity- Fornell-Larcker criterion for SA

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC	0.935										
ESI	0.375	0.859									
FC	0.378	0.159	0.898								
ISI	0.561	0.699	0.233	0.910							
MUX	-0.119	0.195	0.002	0.050	0.826						
EOU	0.411	0.162	0.518	0.223	-0.126	0.762					
RA	0.559	0.359	0.367	0.475	0.010	0.454	0.843				
TR	0.191	0.134	0.310	0.106	0.357	0.289	0.193	0.786			
TSP	0.692	0.410	0.416	0.545	-0.056	0.445	0.597	0.217	0.814		
TT	0.728	0.414	0.437	0.618	-0.102	0.473	0.612	0.232	0.739	0.809	
VS	0.447	0.666	0.178	0.73	0.109	0.169	0.413	0.061	0.420	0.453	0.861

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

Table 5.21 Discriminant Validity- Fornell-Larcker criterion for UK

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC	0.946										
ESI	0.282	0.949									
FC	0.246	-0.007	0.777								
ISI	0.387	0.545	0.034	0.881							
MUX	-0.431	0.015	-0.071	-0.13	0.806						
EOU	0.288	-0.044	0.556	-0.009	-0.274	0.811					
RA	0.415	0.032	0.333	0.162	-0.272	0.466	0.852				
TR	0.212	-0.057	0.483	0.012	0.06	0.381	0.265	0.897			
TSP	0.504	0.183	0.404	0.25	-0.289	0.435	0.513	0.252	0.769		
TT	0.538	0.148	0.352	0.254	-0.364	0.456	0.598	0.272	0.742	0.793	
VS	0.313	0.569	0.023	0.566	-0.013	0.046	0.104	-0.008	0.181	0.184	0.884

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

5.4.2 Structural Model

Once the reliability and validity of the measurement model were established, the next step was to assess and validate the structural model based on path coefficient(β), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) values. The analysis of the structure model will be discussed in further detail in the next following sections.

5.4.2.1 Path coefficient (β)

A bootstrapping with a total number of 5,000 iterations at a significance level of 0.05 ($p < 0.05$) was used as method for assessing the significance of path coefficient as recommended by Hair et al. (2017). Path coefficient (β) is a statistical measure used primarily to determine the strength of relationships connecting latent variables (Hair et al., 2011). According to Hair et al. (2011), for path coefficient to be significant, p-values, a criterion used to assess the significant levels of path coefficient, should be less than 0.05. As shown in Table 5.22, all of the proposed hypotheses were significantly supported for Saudi Arabia structural model, expect for the following hypothesized relationship between trust in mHealth service and mHealth use anxiety (TT –> MUX), which was rejected. Unlike Saudi Arabia structural model, the results as shown in Table 5.23 reveals that in the United Kingdom structural model, all the proposed hypotheses were significantly supported, except for the relationship between visibility and trust in mHealth service provider (VS –> TSP), which was rejected.

Table 5.22 Path Coefficient Values for Saudi Arabia Sample

	β	**P-Value**	
ESI -> TSP	0.155	0.005	Supported
ESI -> VS	0.304	0.000	Supported
FC -> EOU	0.518	0.000	Supported
FC -> TSP	0.219	0.000	Supported
ISI -> TT	0.276	0.000	Supported
ISI -> VS	0.518	0.000	Supported
MUX -> AC	-0.052	0.100	Not Supported
EOU -> MUX	-0.202	0.000	Supported
EOU -> TT	0.148	0.000	Supported
RA -> TSP	0.417	0.000	Supported
RA -> TT	0.157	0.001	Supported
TR -> FC	0.310	0.000	Supported
TR -> MUX	0.440	0.000	Supported
TSP -> AC	0.340	0.000	Supported
TSP -> TT	0.429	0.000	Supported
TT -> AC	0.471	0.000	Supported
TT -> MUX	-0.108	0.051	Not Supported
VS -> TSP	0.105	0.043	Supported

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

Table 5.23 Path Coefficient Values for the United Kingdom Sample

	β	P-Values	
ESI -> TSP	0.144	0.003	Supported
ESI -> VS	0.371	0.000	Supported
FC -> EOU	0.556	0.000	Supported
FC -> TSP	0.266	0.000	Supported
ISI -> TT	0.076	0.013	Supported
ISI -> VS	0.364	0.000	Supported
MUX -> AC	-0.265	0.000	Supported
EOU -> MUX	-0.212	0.000	Supported
EOU -> TT	0.098	0.010	Supported
RA -> TSP	0.415	0.000	Supported
RA -> TT	0.259	0.000	Supported
TR -> FC	0.483	0.000	Supported
TR -> MUX	0.231	0.000	Supported
TSP -> AC	0.222	0.000	Supported
TSP -> TT	0.547	0.000	Supported
TT -> AC	0.276	0.000	Supported
TT -> MUX	-0.330	0.000	Supported
VS -> TSP	0.049	0.329	Not Supported

Note: AC= mHealth Acceptance; TSPB= Trust in Service Provider Benevolence; TSPC= Trust in Service Provider Competence; TSPI= Trust in Service Provider Integrity; TTR= Trust in mHealth Reliability; TTF= Trust in mHealth Functionality; EOU= Ease of Use; RA= Relative Advantage; TR= Trialability; VS= Visibility; FC= Facilitating Conditions; ISI= Interpersonal Social Influence; ESI= External Social Influence; MUX= mHealth Use Anxiety.

5.4.2.2 Coefficient of Determination (R^2)

The coefficient of determination (R^2) is another statistical measure used to assess the proposed structural model. R^2 is primarily used to measure the explanatory power of the proposed mode by explaining amount of variance explained in the endogenous factor by all the exogenous construct connected with it (Shmueli and Koppius, 2011). R^2 can take on any value between 0 and 1 in which values that are closer to 1 indicate that a greater proportion of variance is accounted for by the model for the endogenous (dependent latent variable) factors (Falk and Miller, 1992). Research prescribes R^2 values of 0.67, 0.33 and 0.19 as substantial, moderate, and weak effect, respectively (Chin, 1998; Henseler et al., 2015). In this research, there are 4 endogenous variables: trust in service provider, trust in service provider, mHealth use anxiety, and mHealth acceptance. As shown in Table 5.24 and Figure 5.2, in the Saudi Arabia sample, the model can explain 65.4% of the variance in trust in service provider, 44.8% of the variance in trust in mHealth service, 19.4% of the variance in mHealth use anxiety, and 58.5% of the variance in mHealth acceptance. In the United Kingdom sample, as shown in Table 5.25 and Figure 5.3, the model can explain 62.5% of the variance in trust in service provider, 35.5% of the variance in trust in mHealth service, 19.2% of the variance in mHealth use anxiety, and 37.5% of the variance in mHealth acceptance.

Table 5.24 Coefficient of Determination for SA

	R Square
AC	0.585
MUX	0.193
TSP	0.448
TT	0.654

Table 5.25 Coefficient of Determination for UK

	R Square
AC	0.375
MUX	0.192
TSP	0.355
TT	0.625

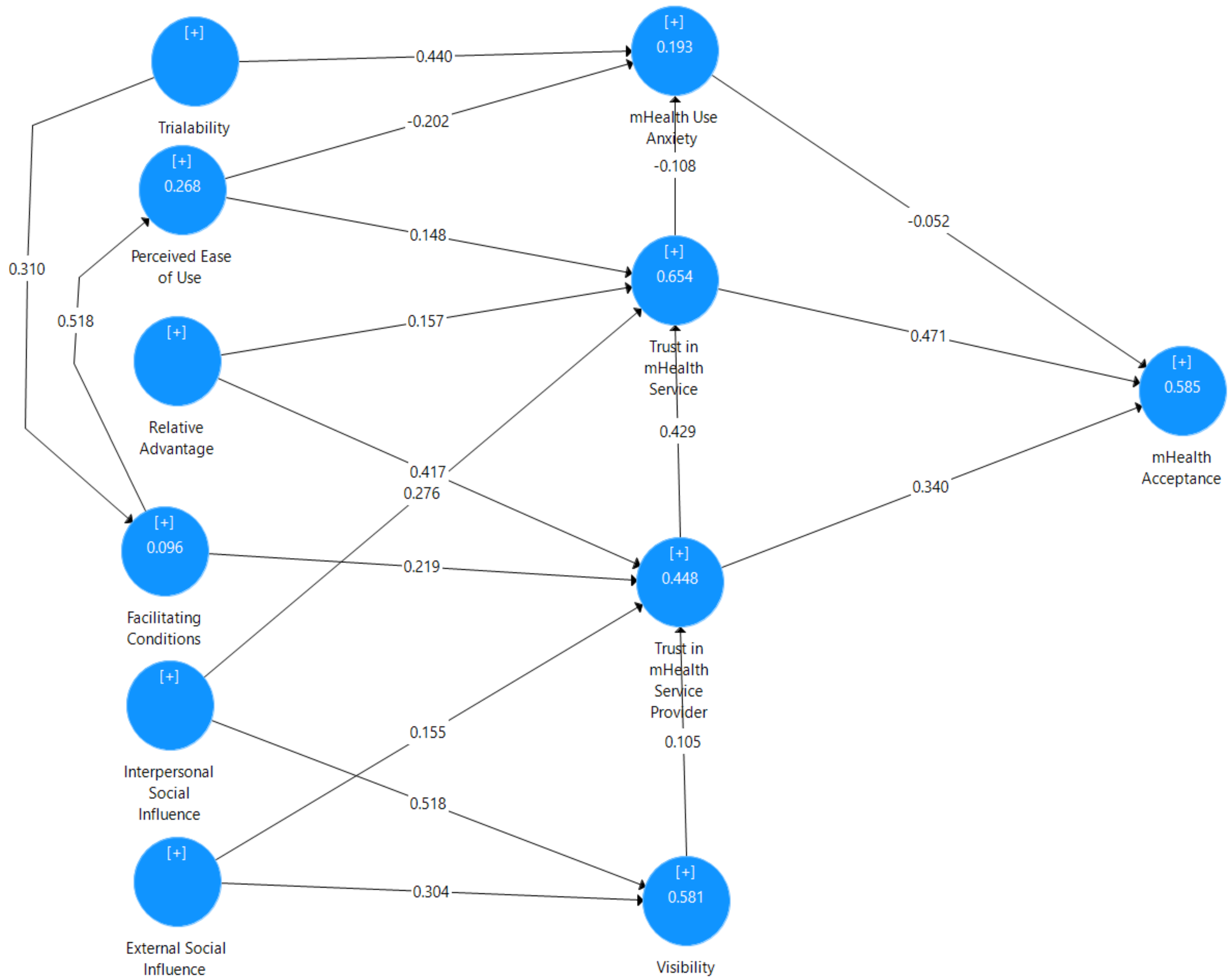

Figure 5.2 SA Path Model Results

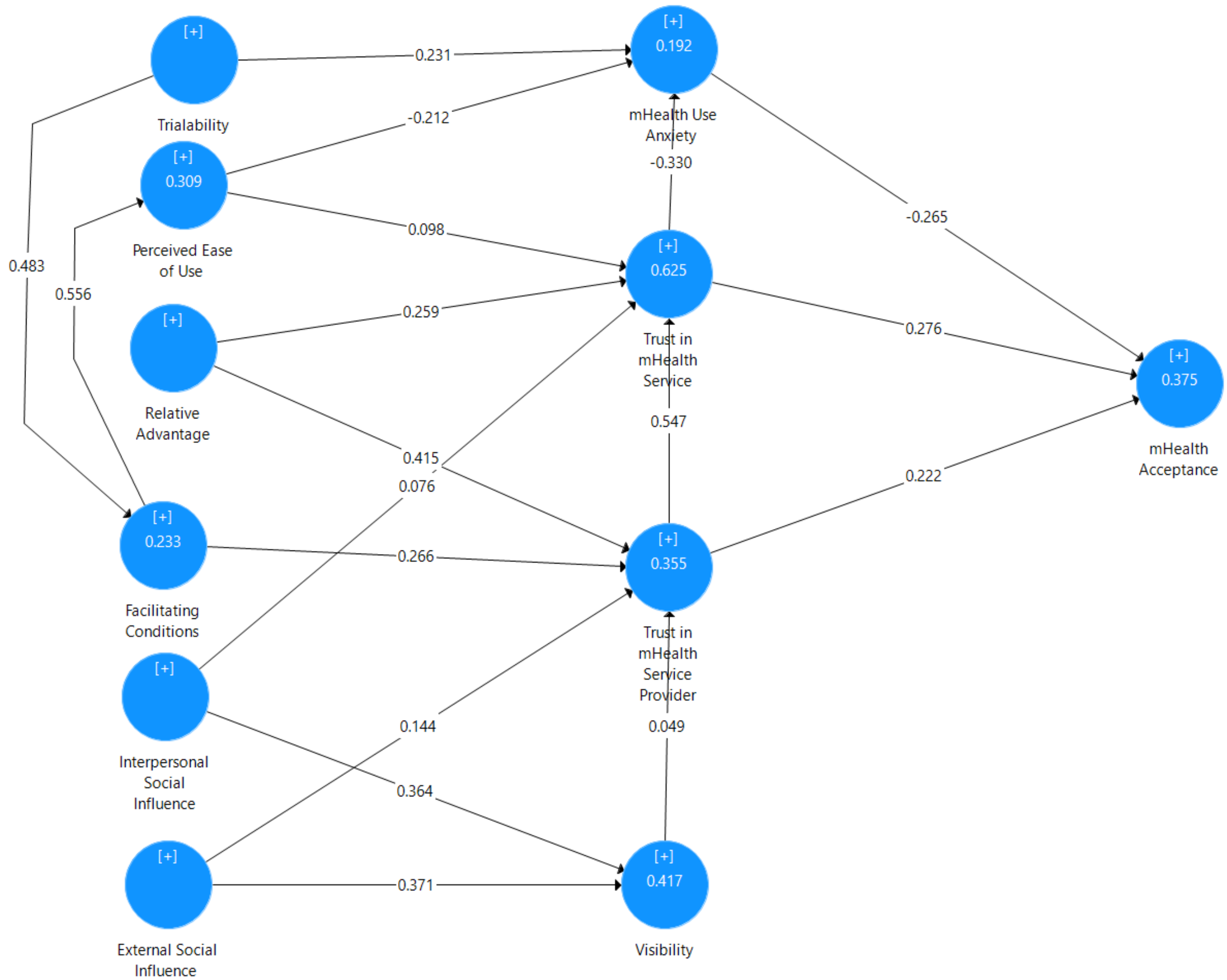

Figure 5.3 UK Path Model Results

5.4.2.3 Effect Size (f^2)

Effect size (f^2) is a statistical measure used to measure the predictive accuracy of the model. According to Hair et al. (2017), the effect size is mainly used to evaluate the extent to which the dependent variable substantially affects the dependent variable when removed from the model. The literature suggests $f2$ values of 0.02, 0.15, and 0.35 as small, medium, and large affects, respectively (Chin, 1998; Cohen, 1988). On the other hand, effect size values that are less than 0.02 is an indicator of no effect (Hair et al., 2017).

The following tables represent the effect size of the exogenous on the endogenous variables. Red values represent weak effects that lack significant effect on its corresponding endogenous variables. On the other hand, black values represent the moderate effect strength the falls between weak and medium, while green values represent the values with largest significant effects. As shown in Table 5.26, in Saudi Arabia, mHealth use anxiety has the weakest effects on mHealth acceptance, while trust in mHealth service provider has the largest effect on mHealth acceptance. On the other hand, interpersonal social influence and trust in mHealth service provider has the largest effect on trust in mHealth service. In terms of trust in mHealth service provider, relative advantages have the largest effect, while visibility has the lowest effect. In terms of mHealth use anxiety, trialability has the largest effect, while trust in mHealth service has lowest effect.

Table 5.26 Effect Size SA

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC											
ESI									0.024		0.113
FC						0.367			0.075		
ISI										0.146	0.326
MUX	0.012										
EOU					0.037					0.047	
RA									0.230	0.040	
TR			0.106		0.217						
TSP	0.111									0.276	
TT	0.192				0.011						
VS									0.011		

For the UK Structural model, as shown in Table 5.27, mHealth use anxiety has the largest effects on mHealth acceptance, while trust in mHealth service provider and trust in mHealth service has a moderate effect on mHealth acceptance. On the other hand, interpersonal social influence and ease of use have the lowest effect on trust in mHealth service, while trust in mHealth service provider and relative advantages have the largest effect on trust in mHealth service. In terms of trust in mHealth service provider, relative advantages have the largest effect, while visibility and external social influence have the lowest effect. In terms of mHealth use anxiety, trialability has the lowest effect, while trust in mHealth service and ease of use have moderate effect on mHealth use anxiety.

Table 5.27 Effect Size SA

	AC	ESI	FC	ISI	MUX	EOU	RA	TR	TSP	TT	VS
AC											
ESI									0.022		0.165
FC						0.448			0.097		
ISI										0.014	0.159
MUX	0.118										
EOU					0.040					0.018	
RA									0.235	0.118	
TR			0.304		0.056						
TSP	0.031									0.521	
TT	0.044				0.105						
VS									0.003		

5.4.2.4 Cross-Validation Redundancy (Q^2)

Another criterion used for assessing the predictive accuracy of endogenous variables is through Stone- Ceisser Q^2 value (Geisser, 1974; Stone, 1974). Cross-Validation Redundancy, also known as predictive relevance (Q^2), is used to measure an indicator of out-of-sample predictive power (Hair et al., 2017). Values of $Q^2 > 0$ indicate that the exogenous constructs have predictive relevance for the endogenous construct under consideration, while Q^2 values lower than 0 indicate lack of predictive relevance (Hair et al., 2017). On the other hand, Chin (1998) and Henseler et al., (2009) suggests that Q^2 values of 0.02, 0.15, and 0.35 indicates that the exogenous variables have a small, medium, and large predictive powers on their corresponding endogenous variables.

As shown in Tables 5.28 and 5.29, all endogenous and exogenous variables were greater than 0.15, except for facilitating conditions and mHealth use anxiety in SA; thereby suggesting an acceptable degree of predictive relevance.

Table 5.28 Constructs Cross-Validation Redundancy for The United Kingdom Sample

	SSO	SSE	Q^2 (=1-SSE/SSO)
AC	1521	947.539	0.377
ESI	1014	1014	
FC	2028	1752.669	0.136
ISI	1521	1521	
MUX	2028	1792.336	0.116
EOU	2028	1631.434	0.196
RA	2028	2028	
TR	1014	1014	
TSP	4056	3230.476	0.204
TT	3042	1869.943	0.385
VS	2028	1375.03	0.322

Table 5.29 Constructs Cross-Validation Redundancy for The Saudi Arabia Sample

	SSO	SSE	Q² (=1-SSE/SSO)
AC	1155	561.033	0.514
ESI	1155	1155	
FC	770	712.323	0.075
ISI	1155	1155	
MUX	1540	1346.334	0.126
EOU	1540	1304.243	0.153
RA	1540	1540	
TR	1155	1155	
TSP	3465	2462.353	0.289
TT	2310	1334.613	0.422
VS	1540	886.677	0.424

5.5 Chapter Conclusion

In this chapter, the pilot and the main results of the proposed research model were discussed. This includes the measurement and structural model results. Table 5.30 shows the results of the 18 hypotheses tested using PLS-SEM in Saudi Arabia and the United Kingdom. The results of the 18 hypotheses are discussed in the next chapter.

Table 5.30 Hypotheses Test Results

Hypothesis	Outcome	
	SA	UK
H1: mHealth use anxiety will negatively affect mHealth acceptance.	Not Supported	Supported
H2: Trust in mHealth service will positively influence mHealth acceptance.	Supported	Supported
H3: Trust in mHealth service will negatively influence mHealth use anxiety.	Not Supported	Supported
H4: Trust in mHealth service provider will positively influence mHealth acceptance.	Supported	Supported
H5: Trust in mHealth service provider will positively influence trust in mHealth service.	Supported	Supported
H6: Trialability will positively affect facilitating conditions.	Supported	Supported
H7: Trialability will positively affect mHealth use anxiety.	Supported	Supported
H8: Ease of Use will negatively affect mHealth use anxiety.	Supported	Supported
H9: Ease of Use will positively affect users trust in mHealth service.	Supported	Supported
H10: Relative advantage will positively affect trust in mHealth service provider.	Supported	Supported
H11: Relative advantage will positively affect trust in mHealth service.	Supported	Supported
H12: Visibility will positively affect users' trust in mHealth service provider.	Supported	Not Supported
H13: Facilitating conditions will positively affect trust in mHealth service provider.	Supported	Supported

H14: Facilitating conditions will positively affect perceived ease of use.	Supported	Supported
H15: Interpersonal social influence will positively affect trust in mHealth service.	Supported	Supported
H16: External social influence will positively affect trust in mHealth service provider.	Supported	Supported
H17: Interpersonal social influence will positively affect visibility.	Supported	Supported

Chapter 6: Discussion

The previous chapter elaborates on the data analysis results and examines the factors forming individuals mHealth acceptance behavior form a technology-anxiety perspective in Saudi Arabia and the United Kingdom. Partial Least Square Equation Modeling approach was used to examine the hypothesized relationships among the proposed research model construct. In this chapter, the results presented in Chapter 5 are discussed. This chapter consists of three parts. Section 6.1 presents an overview of the proposed research model. Section 6.2 discusses the results of the hypothesized relationships among the proposed research model construct in detail. Section 6.3 concludes the discussion chapter.

6.1 The Proposed Research Model

As discussed in Chapter 3, this study proposes a theoretical model that attempts to investigate individuals' mHealth acceptance behavior from a trust-anxiety perspective. Such a perspective utilizes the cognitive-emotional paradigm to explain potential adopters' mHealth use intentions. The rationale behind the proposed model is that with the deficiency of firsthand experiential data, which usually starts to develop once individuals have downloaded and configured mHealth apps on their smartphones or tablets, individuals mHealth acceptance decisions become more likely to be dominated by the emotional responses mHealth evokes and the subjective cognitive beliefs individuals form around mHealth technology in its early stages.

The proposed research model depicts potential adopters' mHealth acceptance behavior as a function of three factors: mHealth use anxiety, trust in mHealth service, and trust in mHealth service provider. This is largely due to the dual role individuals play in mHealth service environments as IS users and mHealth customers (Komiak and Benbasat, 2006; Koufris, 2002). Unlike in face-to-face offline healthcare channels, in mHealth channels, individuals need to use mHealth technology to transmit their personal, including their health data, information electronically to service providers over mobile networks in order to receive their health services. The impersonal nature of mHealth services, therefore, may raise factors such as trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety as issues when accepting mHealth services for the first time, particularly when potential adopters develop concerns around service provider’s benevolence and integrity, the confidentiality of their disclosed information, and the quality and reliability of healthcare services and information provided through mobile terminals. Accordingly, this study conceptualizes trust as a cognitive belief that promotes potential adopters' mHealth use intention and further differentiates between individuals' trust in mHealth services and their trust in mHealth service providers. On the other hand, this study conceptualizes mHealth use anxiety as a negative emotional reaction that can inhibit potential adopters mHealth use intention.

Given that trust and anxiety in the pre-initial interaction stage with the service are dynamic in their nature in that they can be affected by external forces surrounding individuals in the behavioral context, this research, therefore, draws on innovation attributes, external and interpersonal social influence, and facilitating conditions from innovation diffusion, social psychology, and IS research to provide a comprehensive understanding of the social, technological, and behavioral factors affecting mHealth acceptance behavior from a trust-anxiety perspective.

6.2 Discussion of Hypothesis Test Results

6.2.1 Determinants of mHealth Acceptance

Based on the hypothesized research model, individuals acceptance of mHealth services is assumed to be affected cognitively by the level of potential adopters trust in mHealth service and trust in mHealth service provider and emotionally by the level of mHealth use anxiety. The following sections will discuss the results of these hypotheses in further detail.

6.2.1.1 Impact of mHealth Use Anxiety on mHealth Acceptance (H1: MUX→AC)

The uncertainties surrounding mHealth use environment in terms of its service provider behavior have created a fertile ground for mHealth use anxiety to flourish. While previous studies have focused on the anxiety individuals develop due to their fears of being unable to use mHealth as a technological tool in general (known as technology anxiety), the anxiety individuals develop due to their fears of losing their information confidentiality has been largely neglected in the existing mHealth acceptance literature. Given the sensitive nature of healthcare services and health data, this research therefore focuses on mHealth use anxiety as an anxiety factor related to mHealth settings.

The results in Saudi Arabia and the United Kingdom partially support the negative relationship between potential adopters mHealth use anxiety and their mHealth use intention. The results showed that potential adopters mHealth use intention in the United Kingdom was largely inhabited by mHealth use anxiety. Accordingly, this indicates that in the United Kingdom when individuals feel anxious about using mHealth services, they are less likely to use them in the future, despite their advantages, due to the fear of losing control of their sensitive information confidentiality. However, in Saudi Arabia, the negative effect of mHealth use anxiety on mHealth acceptance was not significant. This is a surprising finding since Saudi Arabia is a high uncertainty avoidance culture (Hosted, 1980). People in Saudi Arabia have long been found to exhibit high levels of anxiety toward the use of information technologies, whether they were new or experienced users, due to social and cultural backgrounds (Al-Ghatani et al., 2004). Accordingly, one possible explanation for the insignificant relationship between mHealth use anxiety and mHealth acceptance can be traceback to Saudi Arabia 2030 Vision. In an effort to accelerate the speed of the services provided to Saudi Arabia residents, the government has digitalized all of its transactions, including those in the health, business, and education industries. With the high exposure to online services use in Saudi Arabia, individuals have become more used to the use of mobile services in their lives and thereby developing less anxieties toward the use of highly personalized innovative services, such as mHealth.

6.2.1.2 Impact of Trust in mHealth Service on mHealth Acceptance and mHealth Use Anxiety (H2: TT→AC; H3: TT→MUX)

According to the results in Saudi Arabia and the United Kingdom, a positive and significant relationship exists between trust in mHealth service and mHealth use intention. Such results concur with Meng et al. (2019) findings in mHealth acceptance literature. The study of Meng et al. (2019) showed that when potential adopters thought that mHealth services were trustworthy, they developed a positive intention toward the use of mHealth services in China. Furthermore, the results suggest that, compared to trust in mHealth service provider, trust in mHealth service has a larger effect on individuals mHealth use intention in Saudi Arabia and the United Kingdom. This suggests that when considering the acceptance of mHealth services for the first time, potential adopters are more concerned with the reliability and functionality of mHealth services than the integrity, benevolence, and competence of the service provider itself.

Furthermore, in terms of the relationship between trust in mHealth service and mHealth use anxiety, the results support our hypothesis in the United Kingdom but not in the Saudi Arabia context. For example, the study found a strong negative relationship between trust in mHealth service and mHealth use anxiety. Such findings suggest that potential adopters' trust in mHealth functionality and reliability can significantly mitigate their mHealth use anxiety when accepting mHealth services in the United Kingdom. On the other hand, in Saudi Arabia, no relationship has been found between one's trust in mHealth service and mHealth use anxiety. This may imply that mHealth use anxiety in Saudi Arabia is not directly related to their trust in mHealth services.

6.2.1.3 Impact of Trust in mHealth Service Provider on mHealth Acceptance and Trust in mHealth Service (H4: TSP→AC; H5: TSP→TT)

Consistent with earlier findings in mHealth acceptance literature, trust in mHealth service provider has been found to have a positive and significant effect on potential adopters' mHealth use intention. This finding is in line with the findings of Guo et al. (2016), Deng et al. (2018), and Fox et al. (2018) studies in mHealth acceptance literature. For instance, in China, Guo et al. (2016) and Deng et al. (2018) have found a positive and significant association between one's trust in a mHealth service provider and his/her mHealth use intention. A similar result has been noted in Ireland and the United States by Fox et al. (2018), in which mHealth acceptance was found to be significantly influenced by the level of potential adopters' trust in mHealth service provider. Similarly, this study has found a strong and positive relationship between potential adopters' trust in mHealth service provider and mHealth use intention in Saudi Arabia and the United Kingdom. Accordingly, the findings of this study emphasize the importance of developing potential adopters' trust in mHealth service provider, especially when potential adopters lack direct experience with mHealth services. The findings further suggest that trust in mHealth service provider can not only increase one's mHealth use intention but can also boost one's trust in its mHealth service in Saudi Arabia and the United Kingdom. A finding that is in line with swift trust theory and trust transfer theory. Swift trust theory suggests that individuals can quickly form their trust in others by making quick inferences from available information. On the other hand, trust transfer theory generally suggests that one's trust in one entity can be affected by their level of trust in another entity cognitively by transferring their trust in one entity to another. This implies that in the pre-initial interaction stage with mHealth services, trust in mHealth service provider can serve as an informational cue to build potential adopters' trust in mHealth service.

6.2.2 Factors Affecting Potential Adopters’ Trust and Anxiety

6.2.2.1 Impact of Trialability on mHealth Use Anxiety and Facilitating Conditions (H7:TR→MXU; H6:TR→FC)

The findings of this research validate the positive relationship between trialability and mHealth use anxiety in the United Kingdom and Saudi Arabia, a relationship that has received limited attention in the current mHealth acceptance literature. Such a finding suggests that while trialability can lessen potential adopters’ doubts about how mHealth service may work, it may also increase potential adopters' mHealth use anxiety due to the fears of losing control of their sensitive information confidentiality. This is a surprising finding since it contradicts a widely held assumption by earlier IS researchers in the acceptance and use behavior of new technologies research about the positive role trialability plays in alleviating potential adopters’ early stages anticipated risks and fears (Tylor and Todd, 2000; Al-Jabri et al., 2012; Rogers et al., 2014). One possible explanation for the positive relationship between trialability and mHealth use anxiety can be traced back to the personalized nature of mHealth services. Given that mHealth services are a personalized services that operate primarily on the data one supplies to the system, potential adopters may view the release of their personal information, that includes their health data, via wireless networks to mHealth services as a risky action especially in the light of the increased reports of data breaches and cyber-attacks in the healthcare industry. By providing evidence of the role trialability plays in mHealth use anxiety, this finding has extended our current understanding of the role trialability plays in the early stages of the adoption process of mHealth services. Moreover, this study further investigates the positive relationship between trialability and facilitating conditions, which has been confirmed for both the United Kingdom and Saudi Arabia samples. Such a finding suggests that when accepting mHealth services for the first time, trialability could serve as a technology use enabler.

6.2.2.2 Impact of Ease of Use on mHealth Use Anxiety and Trust in mHealth Service (H8: EOU→MXU; H9: EOU→TT)

Another relationship that has received less attention in earlier mHealth acceptance research is the negative relationship between ease of use and mHealth use anxiety. Drawing on the research findings on Saudi Arabia and the United Kingdom, our earlier assumptions have been confirmed, suggesting that potential adopters' general perceptions about mHealth ease of use can significantly mitigate their mHealth use anxiety when accepting mHealth services. This indicates that when potential adopters lack direct experience with a given mHealth service, they tend to rely on their general estimations about the effort involved in using mHealth service and consequently use it as a strategy to cope up with mHealth use anxiety. This finding is partly in line with Keith et al. (2015) findings. Keith et al.'s (2015) findings indicate that when potential adopters believe that they will be able to control the use of a new mobile service, they also tend to believe in their ability to control any potential risks associated with the release of their personal information over mobile platforms (Keith et al., 2015). This implies that ease of use perceptions can mitigate early stages mHealth use anxiety by affecting potential adopters' personal interpretations of their likelihood to lose control of their confidential information when using mHealth services.

In terms of the relationship between ease of use and trust in mHealth service, the findings of this research share some similarities and differences with earlier findings in mHealth acceptance context. For example, the study of Meng et al. (2019) has found no association between ease of use and trust in mHealth service in China, while the findings of this research have found a significant positive relationship between perceived ease of use and trust in mHealth service in Saudi Arabia and the United Kingdom. Such differences could be traced back to the research sample used in measuring the relationship between the two constructs. Unlike the study of Meng, in which the relationship has been measured from the perspective of both mHealth service provider professionals and patients, this research has measured it primarily from the perspective of mHealth patients. Compared to the perspective of service providers professionals, who are somewhat experienced with online health technologies based on their work experience, patients as potential adopters may have varying degrees of technology ease of use experiences, which is often reflect on their early ease of use perceptions. Our findings are in line with Alsajjan and

Dennis (2010) results in online banking context, which suggests when individuals believe that they can manage the use of a new technology, they tend to develop higher levels of trust in the technology. Overall, the result of the current study illustrates that if potential adopters perceive that mHealth will be easy to use, potential adopters trust in mHealth services is more likely to increase.

6.2.2.3 The Impact of Relative Advantage on Trust in mHealth Service Provider and Trust in mHealth Service (H10: RA→TSP; H11: RA→TT)

This research also proves that there exists a significant positive relationship between relative advantage and potential adopters trust in mHealth service and mHealth service provider in the United Kingdom and Saudi Arabia findings. These findings are consistent with the views of Koufaris et al. (2004) in the online trust literature, who suggest that relative advantage can significantly contribute to the formation of trust even before the actual use of the system. In the mobile banking context, Kim et al. (2009) found that relative advantage has significantly boosted potential adopters' trust in mobile banking in Korea even before the initial interaction stage with the service. Similarly, Susanto et al. (2013) have found a strong positive relationship between potential adopters' trust in internet banking service provider and relative advantage in Indonesia. In line with these studies, this research confirms the significant relationship between relative advantage and trust in mHealth service and its service provider before the initial interaction stage with the service. Yet, when investigating the impact of relative advantage on potential adopters' trust in mHealth service and mHealth service provider simultaneously, the results indicate that relative advantage has less impact on trust in mHealth service compared to its impact on trust in mHealth service provider in both the United Kingdom and Saudi Arabia samples. Accordingly, these discoveries confirm earlier findings in an online banking context and further extend them by investigating the impact of relative advantage on potential adopters' trust in mHealth service provider and mHealth service in the United Kingdom and Saudi Arabia concurrently.

6.2.2.4 Impact of Visibility on Trust in mHealth Service Provider (H12: VS→TSP)

The findings further provide supporting evidence about the significant relationship between visibility and potential adopters' trust in mHealth service provider, a relationship that has not been investigated before in mHealth trust context. The findings suggest that visibility can play a significant role in forming potential adopters' trust in mHealth service provider in Saudi Arabia. When potential adopters notice the usability of mHealth services among their peers in their social surroundings, they are more likely to form positive expectations about mHealth service provider integrity, benevolence, and competence. On the other hand, for the United Kingdom mHealth potential adopters, visibility shows no effect on individuals trust in mHealth service provider. Such a finding suggests that in the United Kingdom, visibility is less likely to affect one's trust in mHealth service provider in the pre-initial interaction stage. This is a surprising finding since visibility is a form of informational cue that acts as a strong signal of service provider trustworthiness. One possible explanation for such a negative relationship could be traced back to the United Kingdom results is that in western cultures such as that of the United Kingdom, people are more individualistic in their decision making and judgment styles in that they tend to be less affected by others as suggested by Hofstede (2001).

6.2.2.5 Impact of Facilitating Conditions on Trust in Service Provider and Ease of Use (H13: FC→TSP; H14: FC→EOU)

This research found that facilitating conditions can significantly boost potential adopters' trust in mHealth service provider at the pre-initial interaction stage in Saudi Arabia and the United Kingdom. According to the hypothesis testing results, facilitating conditions work as an informational cue on which potential adopters can rely to build favorable expectations about mHealth service providers' behavior. Such perceptions largely stem from one's general experience about the external resources and support that online service providers would provide to first time users. If potential adopters believe that they will be technically supported or that they will have access to the necessary resources to use mHealth services, they will be more likely to build positive expectations about mHealth service provider's behavior in terms of its competence, benevolence, and integrity. In addition to positively affecting potential adopters' trust in mHealth service provider, facilitating conditions have been proven to be affective in increasing potential adopters' perceptions of mHealth ease of use in Saudi Arabia and the United Kingdom. This finding is in line with Venkatesh et al. (2000) findings in the workplace context. Accordingly, the current findings of this research have extended this relationship to mHealth acceptance context at the customer level.

6.2.2.6 Impact of Interpersonal Social Influence on Trust in mHealth Service and Visibility and Impact of External Social Influence on Trust in mHealth Service Provider and Visibility (H15: ISI→TT; H17: ISI→VS H16: ESI→TSP; H18: ESI→VS)

Consistent with prior research (Alsajjan et al., 2010; Lei et al., 2008; Chaouali et al., 2016), this research found a significant positive relationship between interpersonal social influence and trust in mHealth service. As predicted, when individuals feel that the use of mHealth is supported by the members of their referent group, they are more likely to form positive expectations toward mHealth service in terms of their reliability and functionality. While the significant relationship has been confirmed in this research, which is in line with prior research findings in the pre-initial interaction stage (Alsajjan et al., 2010; Lei et al., 2008; Chaouali et al., 2016), the research further discovers that in the United Kingdom, the effect of interpersonal social influence on trust in mHealth has the weakest effect among other factors affecting individuals trust in mHealth service before the initial interaction stage with the service. Unlike in the United Kingdom, in Saudi Arabia, the findings found that interpersonal social influence represented the second largest factor contributing to the formation of potential adopters' trust in mHealth services after trust in mHealth service provider.

While the importance of social influence on trust has been acknowledged by earlier researchers in the pre-initial interaction stage, it has been primarily explored from a normative perspective. However, social influence from the informative perspective has been largely neglected in the current mHealth acceptance research, including trust in the pre-initial interaction stage literature. As one form of social influence, the study confirms the significant positive relationship between external social influence and trust in mHealth service provider at the pre-initial interactions stage. In the United Kingdom, the results suggest that potential adopters' trust in mHealth service is largely affected by media reports and advertisements. On the other hand, in Saudi Arabia, the results suggest that while external social influence is significant, its effect on individuals trust in mHealth service provider before the initial interaction stage with the service is relatively low compared to the effect of relative advantage and facilitating conditions. This may indicate that in Saudi Arabia, potential adopters emphasis more importance on relative advantage and facilitating conditions perceptions when forming their trust in mHealth service provider.

The results further confirm the significant and positive relationship between interpersonal social influence, external social influence, and visibility in Saudi Arabia and the United Kingdom. Such results may suggest that individuals’ perceptions of the level of to which mHealth is used among their peers in their social surroundings are largely influenced by the level of mHealth use endorsement by interpersonal social groups, media reports, and media advertisements.

6.3 Empirical Findings and Research Questions

As noted previously, the prime objective of this study was to provide a comprehensive understanding of potential adopters’ mHealth acceptance behavior from a trust-anxiety perspective. This objective has been achieved by developing a theoretical model that explains the role trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety play in individuals’ acceptance of mHealth services and the factors influencing these factors in the pre-initial interaction stage with the service. The theoretical model was then tested and validated in Saudi Arabia and the United Kingdom. The results of the empirical findings of this study will be discussed in further detail according to their research questions in the following sections.

6.3.1 Research Question 1: What are the key factors affecting potential adopters trust in mHealth services and their service providers before the initial interaction stage with mHealth service?

The findings of this research identify relative advantage as one of the key factors affecting potential adopters trust in mHealth service providers before the initial interaction stage with the service. Specifically, the results suggest a strong positive relationship between potential adopters' perceptions of mHealth's relative advantage and their trust in mHealth service provider in Saudi Arabia and the United Kingdom. Such findings imply that relative advantage is one of the leading factors boosting potential adopters trust in mHealth service provider when they lack credible and meaningful information about mHealth service provider behavior. Further, the results identify facilitating conditions as the second largest key factor promoting potential adopters trust in mHealth service providers before their initial interaction stage with the service in Saudi Arabia and the United Kingdom. While external social influence represents another key factor significantly affecting potential adopters trust in mHealth service in both Saudi Arabia and the United Kingdom, its effect on potential adopters trust in mHealth service is relatively smaller than the effect of relative advantage and facilitating conditions on trust in mHealth service provider when accepting mHealth services. This may suggest that potential adopters trust in mHealth service provider before the initial interaction stage with the service is significantly influenced by potential adopters' general perceptions of mHealth's relative advantage and facilitating conditions and by information exchanged by media reports and advertisements. On the other hand, the findings suggest that visibility can increase potential adopters trust in mHealth service provider in Saudi Arabia, while in the United Kingdom, visibility has no influence on potential adopters trust in mHealth service provider before their initial interaction stage with the service. This may imply that in individualistic cultures such as the United Kingdom, potential adopters trust in mHealth service provider is less likely to be influenced by the number of mHealth users around them in their social surroundings.

On the other hand, the findings suggest trust in mHealth service provider as the largest key factor affecting potential adopters trust in mHealth service before the initial interaction stage with the service. Such findings in Saudi Arabia and the United Kingdom indicate that potential adopters' perceptions about mHealth service provider attributes can significantly influence their perceptions about service providers' mHealth service technical attributes when accepting mHealth services. This implies that in the absence of first-hand experience, potential adopters are more likely to rely on their perceptions of mHealth service provider attributes to build their perceptions about mHealth service technical attributes. On the other hand, while the findings identify a positive and significant relationship between relative advantage, interpersonal social influence, ease of use, and trust in mHealth service, the strength of these factors on potential adopters trust in mHealth service relatively differs among Saudi Arabian and United Kingdom potential adopters. For example, relative advantage has been identified as the second largest key factor affecting potential adopters trust in mHealth service in the United Kingdom. However, in Saudi Arabia, interpersonal social influence represents the second key factor affecting potential adopters trust in mHealth service before their initial interaction stage with the service. This may suggest that while relative advantage, interpersonal social influence, and ease of use factors can significantly boost potential adopters trust in mHealth services before the initial interaction stage with mHealth service, the strength of these key factors on potential adopters trust in mHealth service may slightly differ across cultures.

6.3.2 Research Question 2: What are the factors affecting potential adopters mHealth use anxiety when accepting mHealth services?

Based on the empirical findings in Saudi Arabia and the United Kingdom, this research identifies trialability as one of the factors promoting potential adopters mHealth use anxiety when accepting mHealth services. According to this finding, when considering the acceptance of mHealth service for the first time, personal trials of mHealth services may increase potential adopters' anxiety about losing control of their information confidentiality before their initial interaction stage with the service. Moreover, the results also suggest that ease of use, on the other hand, can negatively affect individuals mHealth use anxiety when accepting mHealth services. Such findings in Saudi Arabia and the United Kingdom may imply that potential adopters perceptions of mHealth usability can decrease their information confidentiality loss fears even before their initial interaction stage with the service. In addition to ease of use, the results in the United Kingdom identify trust in mHealth service as another factor mitigating potential adopters mHealth use anxiety when accepting mHealth services. Such results suggest that while trialability can increase potential adopters mHealth use anxiety before their initial interaction stage with the service, ease of use may decrease it. The results further suggest that in individualistic cultures such as the United Kingdom, one's trust in mHealth service can also reduce one's mHealth use anxiety when accepting mHealth services.

6.3.3 Research Question 3: To what extent does trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety affect potential adopters’ acceptance of mHealth services?

The empirical investigations in Saudi Arabia and the United Kingdom identify trust in mHealth service as the largest factor affecting potential adopters’ acceptance of mHealth services. Moreover, compared to the effect of trust in mHealth service, the findings demonstrate that trust in mHealth service provider exerts lower effects on potential adopters’ acceptance of mHealth services than does trust in mHealth service. This implies that when accepting mHealth services, potential adopters are generally more concerned with mHealth technology performance than with mHealth service providers behavior, which often reflects on their acceptance behavior. On the other hand, the empirical evidence in Saudi Arabia and the United Kingdom suggests that mHealth use anxiety is not a major concern for potential adopters when accepting mHealth services in Saudi Arabia. However, in the United Kingdom, mHealth use anxiety represents the second largest factor affecting potential adopters acceptance of mHealth services before their initial interaction stage with the service. Accordingly, the results may suggest that when accepting mHealth services, potential adopters’ mHealth use intentions are largely affected by their level of trust in mHealth service and their trust in mHealth service provider. However, in individualistic cultures such as the United Kingdom, potential adopters’ acceptance of mHealth services can also be affected by their level of mHealth use anxiety before their initial interaction stage with the service.

6.4 Chapter Conclusion

In this chapter, the results of the 18 hypotheses developed for this study are discussed from three aspects. First, it explores whether the test results verify or deepen our understanding of the key factors used to predict mHealth acceptance behavior from a trust-anxiety perspective. It also investigates the effectiveness of the factors used in the model to predict the environmental factors affecting individuals trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety. Second, similarities and differences between the test results and findings from earlier studies in mHealth acceptance, trust, innovation diffusion, and IS research has been discussed to gain further insights into potential adopters mHealth acceptance behavior. Third, a rational explanation of the results has been given to deepen the understanding of mHealth acceptance behavior from a trust-anxiety perspective.

Chapter 7: Conclusion

Chapter 7 is the final chapter of this thesis. It consists of two sections. Section 7.2 discusses the contributions of this research from two perspectives, namely, the theoretical contribution and the practical implications. Section 7.3 and 7.4 discuss the limitations of this research and provide further suggestions for future research.

7.1 Contributions

7.1.1 Theorical Contributions

This research makes several theoretical contributions. First, this study proposes a trust-anxiety model to explain potential adopters' acceptance of mHealth services, which serves as an extension of previous investigations on trust and anxiety in mHealth acceptance research. While previous studies have generally recognized the overall impact of trust and anxiety factors on individuals' mHealth use intentions (Guo et al., 2016; Houqe et al., 2017; Fox et al., 2018), less attention has been devoted to understanding potential adopters' acceptance of mHealth services from a trust-anxiety perspective. As mHealth represents an innovative technology for most of its potential adopters, it is more likely that the adoption experience of mHealth services will be dominated by internal psychological cognitive beliefs and negative emotional reactions, such as trust and anxiety, in its early stages due to the increased uncertainties surrounding mHealth use environment in terms of its performance and its service provider behavior. Accordingly, this research builds on previous trust and anxiety findings in mHealth acceptance research and extends it by developing a trust-anxiety model. Specifically, this study extends prior trust investigations by distinguishing between trust in mHealth service and trust in mHealth service provider and examining their combined effect on mHealth use intention, which has been rarely explored in a single model. Moreover, unlike previous mHealth acceptance studies that focuses on individuals' technology anxiety (Houqe et al., 2017; Rajak et al., 2021), this research incorporates mHealth use anxiety as a new contextual anxiety factor related to mHealth services and examines its negative effects on potential adopters mHealth use intentions. The findings in Saudi Arabia and the United Kingdom demonstrate that trust in mHealth service exerts larger effect on mHealth use intention than trust in mHealth service provider. mHealth use anxiety, on the other hand, exerts large negative effects on potential adopters mHealth use intentions in the United Kingdom. For future researchers with interests in studying potential adopters' acceptance behavior of new personalized technologies like mHealth services, the research model may serve as a strong reference.

Second, while prior research in IS acceptance has long recognized the dynamic nature of individual anxiety as an emotional reaction (Thatcher and Perrew, 2002; Marakas et al., 2000), yet the factors affecting potential adopters’ anxiety before their initial interaction stage with mHealth services remain unexplored in the existing mHealth acceptance literature. This research, therefore, fills in this gap by exploring the effects of trialability and ease of use from innovation diffusion theory and trust in mHealth service from a trust perspective on mHealth use anxiety. The findings reinforce previous IS claims about the dynamic nature of individuals anxiety and depict trialability as an mHealth use anxiety promoter, while ease of use as an inhibitor in Saudi Arabia and the United Kingdom. It further discovers that trust in mHealth service can mitigate potential adopters’ mHealth use anxiety in the United Kingdom when accepting mHealth services. To the author’s best knowledge, this is the first study to investigate the factors affecting individuals' anxiety in mHealth acceptance research. Accordingly, this research advances the current understanding of individuals anxiety in mHealth acceptance research by emphasizing its dynamic nature and opens a new path for future research in the literature to explore the factors affecting potential adopters’ anxiety when accepting mHealth services.

Third, while the importance of trust in mHealth service and trust in mHealth service provider has gained increased interest in mHealth acceptance research, less consideration has been given to the factors underlying their development before the initial interaction stage with the service. Further, current studies on trust in mHealth acceptance research focus on the technological, institutional, and personal factors promoting individuals trust, yet none of the existing mHealth trust studies have explored individuals trust promoters from social and behavioral dimensions. As individuals trust in the early stages of the mHealth adoption process is largely influenced by first impression cues and second-hand information available around them (McKnight et al., 2002), social factors like external social influence and interpersonal social influence and behavioral factors like facilitating conditions can constitute the knowledge base on which individuals trust in mHealth service and trust in mHealth service provider are formed as they serve as environmental stimuli. By incorporating factors from social and behavioral dimensions, a better understanding of trust promoters in mHealth acceptance research can be provided. The results in Saudi Arabia and the United Kingdom validate our views and demonstrate that individuals' trust in mHealth service provider is not only promoted by technological factors but can also be promoted by behavioral factors such as facilitating conditions and social factors such as external social influence. Trust in mHealth service provider in turn, can enhance individuals trust in mHealth service along with interpersonal social influence. Therefore, it is believed that this research enriches the current mHealth trust literature, which is mostly focused on technological, institutional, and personal factors by incorporating social and behavioral factors.

Fourth, different from prior studies that have utilized the notions of traditional IS acceptance and use models, such as UTAUT and TAM, to capture trust promoters from a technological dimension. This research has employed relative advantage, ease of use, and visibility from innovation diffusion theory as predictors of individuals trust in mHealth service and its service provider. Unlike traditional IS acceptance and use models, which assume that individuals trust is primarily a function of two technological attributes (e.g., perceived ease of use and perceived usefulness), IDT provides a richer set of technological attributes like visibility and relative advantage, which can provide further insights into mHealth technological promoters. The results of this research show that potential adopters trust in mHealth service provider can be promoted by relative advantage in Saudi Arabia and the United Kingdom as well as visibility in Saudi Arabia. On the other hand, trust in mHealth service can be largely influenced by potential adopters' perceptions of mHealth's ease of use and relative advantage in both Saudi Arabia and the United Kingdom. Accordingly, this contributes to a better understanding of the promoters of potential adopters' trust in mHealth service provider and its service in mHealth acceptance research and highlights the appropriateness of using innovation attributes from innovation diffusion theory as trust promoters from a technological dimension.

7.1.2 Practical Implications

While the benefits of mHealth services are obvious on the individual and mHealth service provider level, the adoption rates of these services by its intended users are still slow and some of these service are not sustainably operating in the existing healthcare services. Given that the success of these services primarily depends on their massive acceptance by their targeted customers, this research thus can offer mHealth service providers, their markets and IT departments, and other stakeholders, including but not limited, to cooperate application designers and software providers with insightful practical implications to encourage the uptake of their mHealth services.

From a practical perspective, the results emphasize the importance of establishing potential adopters trust in mHealth service and its mHealth service provider to encourage early stages mHealth acceptance behavior. For mHealth service providers to establish their targeted customers' trust in mHealth service, it is important for them to design user friendly systems. The constraints of mobile devices (e.g., small screens and difficult input) highlight the necessity to design highly easy-to-use mHealth interfaces (Lee and Chung 2009). Poor interfaces and difficult to use system features may increase the time and efforts used to operate mHealth services, which may consequently affect the formation of potential adopters' trust in mHealth services. It is also critical for mHealth service providers to develop different interface designs for various mobile phones and tablets operating systems, such as Android, Apple IOS, and Windows Phone, to ensure that the display of these interfaces fits with their mobile devices screens (Goa et al., 2017). Service provides can also establish potential adopters trust in mHealth service by highlighting the advantages of mHealth services over traditional means of healthcare channels. For example, when advertising mHealth services, practitioners can express the benefits mHealth service can provide to its adopter in terms of the speed of access to healthcare services, convenience, costs, and health management effectiveness over traditional healthcare channels, such as doctor visits. Only those who can observe the potential benefits mHealth service can provide to them will form higher levels of trust in mHealth service provider services. The results also emphasize the key role interpersonal communication channels play in the development of individuals' trust in mHealth services. Such influence is primarily exerted through the identification process. For practitioners, this means that it is important to encourage the spread of positive word of mouth among social groups as people tend to be affected by their family, friends, and other potential adopters' opinions and beliefs. Apart from these strategies, the results highlight the importance of trust in mHealth service provider in the development of potential adopters' trust in mHealth service, which exerts the greatest effect among other factors. When individuals lack sufficient information about service providers mobile services, they tend to rely on their beliefs that were formed around service provider behavior as an informational cue about mHealth service attributes. Thus, practitioners should develop sufficient levels of their targeted consumers trust in mHealth service provider to boost their trust in mHealth service.

To develop potential adopters' trust in mHealth service providers, practitioners should pay close attention to the effects of facilitating conditions. Specifically, a great importance should be attached to customer support services, such as 24/7 online assistant and call centers with a trained customer support staff. A great importance should be also attached to virtual use tutorials and first-time use instructions to improve initial users mHealth use experience. These facilitating conditions should be also advertised to the targeted adopters when advertising mHealth services. Apart from this, the results also emphasize the importance of external social influence on trust in mHealth service provider. This suggests that service providers can enhance their image by advertising the use of mHealth services through media, such YouTube and TV channels, and Radio broadcasts. The results also suggest that when considering the use of mHealth service for the first time, adopters always look for the benefits mHealth service can offer to them over traditional offline means of health services. Accordingly, when introducing mHealth services, practitioners should stimulate these benefits by showing users how the use of mHealth services can lead to these benefits.

In addition to increasing potential adopters trust in mHealth service and trust in mHealth service provider, practitioners should also decrease their targeted customers mHealth use anxiety. While the results suggested a strong positive correlation between trialability and mHealth use anxiety, they also have highlighted the strong positive correlation between trialability and facilitating conditions. This suggests that when designing mHealth services, practitioners should offer first time users with triable features that do not require the use of their personal information (e.g., ID, name, email address, phone number, location) to increase their confidence in using mHealth services on a trial basis. Service providers should also provide first time users with information about their privacy practices and policies. For example, how their customers collected data will be handled and kept confidential at all times. This should also be highlighted to customers when advertising mHealth services to the public. Another way for decreasing individuals mHealth use anxiety levels is by highlighting the usability of mHealth services when introducing first time users to mHealth services and advertising it through the media.

In addition to the practical implications, this study provides several practical benefits to reduce waiting lists in the healthcare sector. By understanding the factors underlying potential adopters' acceptance of mHealth services from a trust-anxiety perspective, health care providers can increase individuals' reliance on mHealth services for managing their health and improving their quality of life. Specifically, the development of individuals trust in mHealth service and its mHealth service provider before the initial interaction stage with the service can increase individuals use of self-diagnosis tools. When individuals increase their use of self-diagnosis tools, they are more likely to decrease their reliance on health professionals for health diagnosis and treatment. Furthermore, by minimizing individuals mHealth use anxiety, health care service providers can increase patients' use of self-monitoring tools. The use of self- monitoring tools can decrease individuals' reliance on doctors and other health professionals to monitor and manage their health and quality of life.

Yet, developing individuals trust in mHealth service, trust in mHealth service provider, and reducing their mHealth use anxiety do not only benefit individuals but can also benefit health care service providers alike. By increasing individuals' uptake of virtual care mHealth services, service providers can handle larger numbers of patients in less time and in a faster way, which helps them better manage their waiting lists. Furthermore, the increase of individuals' reliance on self-diagnosis tools can help healthcare providers to regularly monitor their patients' health and quality of life and provide them with timely medical instructions and treatment routines, which can help them in return to reduce their waiting lists.

7.2 Limitations

Just like with other studies, this research study has its own limitations that need to be addressed when interpreting the findings of this study. In this section, the limitations of this study are discussed from two aspects, namely, cross-sectional design and context generalization.

7.2.1 Limitation of Cross-Sectional Design

In cross-sectional design, data are collected in a single point of time from the targeted population to examine the hypothesized relationships among the proposed variables. However, the everchanging consumer behaviour and the dynamic nature of trust and anxiety in online environments increase the need to adopt a longitudinal study design to capture the factors contributing to changes in potential adopters' trust perceptions and mHealth use anxiety emotional reactions over time and to further verify whether the effect of trust and mHealth use anxiety on mHealth acceptance decisions differ across different points of time.

7.2.2 Limitation of Context Generalization

As this research has been conducted in the cultural settings of Saudi Arabia and the United Kingdom, the results of this study can only be generalized to countries with similar cultural backgrounds. This is because other countries may have different cultural traits and values, which may affect the way in which individuals' perceptions, emotional reactions, and behaviors are formed around the use of mHealth services. Furthermore, the study was conducted in countries with high levels of mHealth market readiness and high percentages of mobile device owners and internet subscribers. Therefore, the findings of this study should be taken with caution when generalizing the findings to other countries with differing levels of mHealth users and market readiness.

7.3 Suggestion for Future Research

Given that mHealth is a relatively new phenomenon, the scope of the developed model for this research needs to be expanded to gain further insights into individuals mHealth acceptance behavior from a trust-anxiety perspective. Particularly, as potential adopters may demonstrate different trust and mHealth use anxiety behavioral patterns in the future, it is important for future research to adopt a longitudinal research design to understand how the factors affecting potential adopters trust perceptions and mHealth use anxiety in the pre-initial interaction stage differ in their importance in the initial interaction stage with the service. Furthermore, as individuals mHealth acceptance behavior across nations is more likely to be affected by cultural factors, such as religion, ethnicity, cultural values, and norms, it will be interesting to investigate the effect of national cultural factors as moderators to gain a better understanding of potential adopters' mHealth acceptance behavior from a trust-anxiety perspective as rooted in the philosophical perspective and understanding of their potential adopters' national culture. Besides this, as there are other factors that might affect potential adopters trust in mHealth service, trust in mHealth service provider, and mHealth use anxiety, such as those related to the service provider and mHealth service themselves (e.g., service provider reputation, service availability, service quality, and service cost). Therefore, further research is required to understand the factors affecting individuals trust and anxiety in mHealth acceptance research from other dimensions to gain a better understanding of mHealth acceptance behavior from a trust-anxiety perspective.

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Appendix A

1) Cover Letter

Dear Participant,

You are invited to participate in a research study conducted by Rawan Alhazmi, a Ph.D. candidate at the University of Manchester, for understanding your point of view on what motivates you to use a mobile health app to receive healthcare services as a substitute to regular face-to-face doctor visits. For example, using a mobile health app to consult a physician remotely instead of visiting it to receive such healthcare service.

Before you decide to take part, it is important for you to be aware of the following:

- You have the right to withdraw from the survey at any point in time that you wish to do so without giving any reasons.
- Once you submit the survey, all your survey responses will be assigned a random ID generated by the survey system enabling your answers to be stored as anonymous data.
- For further information about the study, please read the following document: Participant Information Sheets.
- By submitting the survey, this implies your consent regarding the information in the participant information sheet.

If you have any questions or you are interested in knowing the findings of this research, please feel free to contact me, Rawan Alhazmi, via my email: rawan.alhazmi@postgrad.manchester.ac.uk, or my main supervisor Prof. Dong-Ling Xu email: ling.xu@manchester.ac.uk.

If you are interested in taking part in this study, please provide your consent to the following:

- I confirm that I have read the attached information sheet [Version 2; Date 21/03/2021] for the above study and have had the opportunity to consider the information and ask questions and had these answered satisfactorily.
- I understand that my participation in the study is voluntary and that I am free to withdraw at any time without giving a reason and without detriment to myself.
- I understand that it will not be possible to remove my data from the project once it has been anonymised and forms part of the data set. I agree to take part on this basis.
- I agree that any data collected may be published in anonymous form in academic journals, academic conferences, reports, academic projects, and researcher Ph.D. thesis.
- I understand that there may be instances where during the course of the study, information is revealed which means that the researchers will be obliged to break confidentiality, and this has been explained in more detail in the information sheet.

- I consent to the personal information collected as part of this study being transferred and processed in the UK. This processing will be subject to UK data protection law.
- I agree that I am aged 18 or above and I agree to take part in this study.

Agree	Disagree

2) mHealth Introduction Section

What is Mobile Health?

Mobile health is a clinical healthcare app providing its users with real-time access to therapists, specialists, and NHS doctors via mobile devices like smart phones or Tablets. To use mobile health, all you need to do is to download the application on your mobile device, register your personal information (e.g., name, NHS GP information, credit card information, and/or national health insurance information, etc.), and verify your identity. You can use mobile health for free by registering your national health insurance information/NHS GP information or through paid service.

With mobile health you can do the following:

- To book your medical appointments at any time and day in the week.
- To access therapists, specialists, and NHS doctors via text, video, or phone calls.
- To review/download your medical records (e.g., laboratory results, previous online consultations, etc.).
- To order prescriptions.

However, some mobile health apps may provide you with the following:

- Health check-up tools to monitor and manage your health (e.g., mental health, blood pressure, diabetes).
- Self-disease diagnoses tools to check your symptoms and to know what the next step is.
- Medical Articles.

Here are some examples of available mobile health apps for UK residents to use to receive healthcare services remotely via their mobile devices.

- Babylon
- Push Doctor
- Patient Access
- Livi

Have you used such mobile health apps before like Babylon, Push Doctor, Patient Access, or Livi to receive your healthcare services remotely?

No, I have never used such mobile health apps before
Yes, I have used such mobile health apps before for once
Yes, I have used such mobile health apps from two to five times
Yes, I have used such mobile health apps for more than five times

3) Demographic Information Collection

The demographic information in this section will only be used in aggregated form and will not be used to identify individual respondents. Please select only one item in each category.

What is your Gender?

- Male
- Female

What is your Monthly Income?

What is your Age?

What is your highest level of education?

4) Survey Questions

Page 1:

Q1: All questions in this section reflect your perceptions and opinion about the use of mobile health. On a scale ranging from strongly agree to strongly disagree, to what extent do you agree with each of the following statements?

* You can use one of the above-mentioned mobile health apps examples (Babylon, Push Doctor, Patient Access, Livi) or similar mobile health apps that you have heard/read about to base your answers on.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I would hesitate using mobile health due to the fear of making costly mistakes that I cannot correct.							
When using mobile health, I fear that I might lose my personnel information.							
When using mobile health, I fear that the service provider might share my personal information with others without my permission.							
I feel apprehensive about using mobile health to receive my healthcare services remotely.							
Before deciding whether to use mobile health, I prefer trying it out first for once.							
I want to use mobile health on a trial basis to see what it can do for me.							

I want mobile health to be available for me to try without me having to provide personal information first.								
The use of mobile health would be compatible with my current experience with other mobile apps.								
A technical support center would be available for assistance when I have difficulties in using mobile health.								
A set of use instructions would be available for me while I am using mobile health.								
I could get help from others when I have issues in using mobile health.								
It would be easy for me to configure mobile health on my mobile device.								
Learning how to operate mobile health to conduct healthcare transactions like booking an appointment, consulting a physician, making a payment, etc. would be easy for me.								
I think that the use of mobile health would not require a lot of mental effort.								
Overall, mobile health would be easy to use.								

Using mobile health to receive healthcare services is more convenient than regular doctor visits.								
Mobile health enables me to reach physicians more quickly than regular doctor visits.								
Mobile health provides me with greater control over my health management than regular doctor visits.								
Overall, mobile health is more useful for receiving healthcare services than regular doctor visits because I am less limited by location, time, and transportations.								
In my surroundings, I heard/read that others have used mobile health to manage their health.								
I have heard/read about what others can do using mobile health.								
It is easy for me to notice others in my surroundings using mobile health to receive healthcare services.								
Overall, mobile health is commonly used in my surroundings.								

Page 2:

Q1: All questions in this section reflect your perceptions and opinion about the use of mobile health. On a scale ranging from strongly agree to strongly disagree, to what extent do you agree with each of the following statements?

* Examples of Media are TV, Radio, News, Internet, YouTube, etc.
* You can use one of the above-mentioned mobile health apps examples (Babylon, Push Doctor, Patient Access, Livi) or similar mobile health apps that you have heard/read about to base your answers on.

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I read/saw media reports suggesting that mobile health was a good way to receive healthcare services.							
Media advertisements consistently recommend the use of mobile health.							
Information from the media would influence my opinion about using mobile health.							
People I know (e.g., family, friends, peers, colleagues) think that using mobile health to receive healthcare services is a good idea.							
People whose opinion I value would prefer that I use mobile health for managing my health.							
People I know have recommended that I should try mobile health.							

Page 3

Q2: All questions in this section reflect your perceptions and opinion about the technology of mobile health. When considering using mobile health for receiving healthcare services, on a scale ranging from strongly agree to strongly disagree, to what extent do you agree with the following statements? * You can use one of the above mentioned mobile health apps examples (Babylon, Push Doctor, Patient Access, Livi) or similar mobile health apps that you have heard/read about to base your answers on.							
	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Mobile health would be a reliable piece of application.							
Mobile health would not fail me.							
I can depend on mobile health to receive my healthcare services remotely.							
Mobile health would have the required features for my tasks (e.g., for booking appointments, ordering prescriptions, reviewing medical records, consulting physicians, etc.).							
Mobile health would have the necessary technological functionality to receive healthcare services.							
Mobile health would be able to do what I need.							
Mobile health would be a reliable piece of application.							

Mobile health would not fail me.							
I can depend on mobile health to receive my healthcare services remotely.							
Mobile health would have the required features for my tasks (e.g., for booking appointments, ordering prescriptions, reviewing medical records, consulting physicians, etc.).							
Mobile health would have the necessary technological functionality to receive healthcare services.							
Mobile health would be able to do what I need.							

Q3. All questions in this section refer to your perceptions and opinion about mobile health service provider. On a scale ranging from strongly agree to strongly disagree, to what extent do you agree with each of the following statements?

*** You can use one of the above-mentioned mobile health apps examples (Babylon, Push Doctor, Patient Access, Livi) or similar mobile health apps that you have heard/read about to base your answers on.**

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
Mobile health service provider would be skillful and able to provide its healthcare services remotely.							
Mobile health service provider would provide							

medical advice very effectively.							
In general, Mobile health service provider would be fully qualified in providing healthcare services.							
Mobile health service provider would be concerned about what is best for me.							
If I required help, mobile health service provider would do its best to help me.							
Overall, mobile health service provider would be interested in my well-being, and not just in serving itself such as making money.							
I expect mobile health service provider to provide me with factual information about my health.							
I expect mobile health service provider to honor any commitments it makes.							
I expect mobile health service provider to be honest in how it deals with me.							

Q4. On a scale ranging from strongly agree to strongly disagree, to what extent do you agree with the following statements?

*** You can use one of the above-mentioned mobile health apps examples (Babylon, Push Doctor, Patient Access, Livi) or similar mobile health apps that you have heard/read about to base your answers on.**

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
I plan to install mobile health on my mobile device in the future when I have the chance.							
Given that I had access to mobile health on the app store, I predict that I would try it out.							
Assuming that I had access to mobile health on my device, I intend to use it within the next six months.							