FACTORS INFLUENCING THE ACCEPTANCE OF HEALTHCARE INFORMATION TECHNOLOGIES: A META-ANALYSIS

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Abstract

Healthcare information technologies (HIT) can address several challenges faced by healthcare systems. To benefit from the advantages HIT offer, users must first accept them. This meta-analysis synthesizes previous research on HIT acceptance. It uses data from 214 independent samples reported in 193 articles and 83,619 technology users from 33 countries. The study contributes to the HIT literature by (1) synthesizing the empirical findings on technology acceptance factors and combining them in a comprehensive model, (2) testing the mediating mechanisms of health technology acceptance, and (3) examining contextual differences. The study finds that HIT acceptance depends on various predictors proposed by the technology acceptance model and the unified theory of acceptance and use of technology. These factors displayed strong indirect effects through effort expectancy, perceptions of the technology, performance expectancy, and attitudes toward using HIT. Studies overlooking these effects may underestimate the importance of various acceptance factors. Finally, the results suggest that technology acceptance varies across healthcare technologies (remote information systems [IS], wearables), users (staff/patients, age, voluntariness, experience), and locations (hospitals, healthcare systems, life expectancy in country). We also provide IS managers with guidance for improving technology acceptance in the healthcare industry to ensure efficient, high-quality services.

Keywords: meta-analysis; technology acceptance; healthcare technologies

INTRODUCTION

Healthcare is one of the fastest-growing industries worldwide, and it is estimated that spending on healthcare will reach nearly 20 percent of the United States' GDP by 2025. Global healthcare spending will also increase and double to $18.28 trillion by 2040 (Dieleman et al., 2016). Given these current developments, the healthcare industry faces the challenge of ensuring the delivery of high-quality services that can be provided efficiently and in a timely manner (Chong et al., 2015). The effective use of information systems (IS) is essential for the long-term success of organizations operating in the healthcare industry (Zeadall and Bello, 2019). Electronic health records, radio frequency identification (RFID), blockchain, and cloud computing are just some of the healthcare information technologies (HIT) that the healthcare industry has implemented to improve its performance (Chong et al., 2015; Kohli and Tan, 2016; Tanwar et al., 2020). IS scholars have frequently stressed the importance of implementing new technologies to achieve cost savings and service improvements (Tortorella et al., 2020). The recent COVID-19 pandemic further highlights the key role of IS as healthcare professionals and governments use mobile technologies to track and investigate COVID-19's spread, artificial intelligence tools to forecast how government policies impact the number of COVID-19 cases, and clinical IS to facilitate the clinical management of COVID-19 (Ma et al., 2020).

Given the important role of technologies in improving healthcare processes, rich studies exist that have examined the factors that drive, inhibit, and influence the acceptance of HIT by healthcare professionals or patients. Research has been conducted based on various theories in the fields of psychology, IS, and organizational behavior to study the antecedents of HIT adoption. Appendix A summarizes the recent studies of HIT adoption. The theory of planned behavior, the technology acceptance model (TAM), and the unified theory of acceptance and use of technology (UTAUT) are the dominant theories applied in these studies. Collectively, they have contributed to both the theoretical and practical advancement of our understanding of HIT acceptance. Nevertheless, studies of HIT acceptance have also provided us with multiple competing theoretical perspectives and inconsistent findings. Most of these studies have not applied the complete TAM or UTAUT theories, thus limiting our understanding of their actual boundaries.

For example, Kim et al. (2016) applied both UTAUT and TAM in their study of electronic medical record (EMR) adoption. This presents a problem as UTAUT is a unified model that includes variables from TAM. Thus, their model contains similar variables such as perceived ease of use and effort expectancy. Other TAM and UTAUT studies have reported inconsistent findings on whether predictors, such as perceived usefulness and perceived ease of use, influence physicians and nurses' behavioral intentions (i.e., Escobarrodríguez et al., 2012; Ifinedo, 2016; Kijsanayotin et al., 2009; Kim et al., 2016; Diño et al., 2015). The examples discussed typify the current issues faced by research into HIT adoption. There is a lack of consistent findings with regard to the key drivers of HIT adoption.

Furthermore, it is unclear how these predictors perform in different contexts, such as different types of HIT, locations where the technologies are implemented, and differences among different adopters such as doctors and patients. These studies have focused on finding the best predictors for HIT adoption instead of developing a theoretical understanding derived from a comprehensive theme. With regard to the adoption of existing theories such as TAM or UTAUT, most of these studies have not applied the full model. They have extended the theories by adding HIT adoption antecedents via a piecemeal approach to improve predictability. Thus, researchers studying HIT adoption are unclear about which theoretical framework to use, how to combine or extend them, or which predictors they should focus on. Moreover, HIT adoption researchers encounter challenges with regard to contextual factors (e.g., technology types, user types) that may unknowingly affect the explanatory power of their research models, resulting in findings that may not be consistent or reliable. Against this backdrop, the purpose of this research was to apply a meta-analysis approach to holistically examine findings from previous HIT adoption studies and help provide a better theoretical understanding of the factors that influence HIT adoption. The key objective of this study was to ascertain and clarify the critical predictors of HIT adoption and the moderators of these relationships to understand the contextual differences in HIT adoption. To address the existing inconsistencies in the findings, this study focused on moderators pertinent to the context of HIT. We also compared various competing theoretical models to further advance our theoretical understanding of HIT adoption.

This study is not the first meta-analysis examining HIT adoption. Recent meta-analyses of this issue include studies by Tao et al. (2020) and Chauhan and Jaiswal (2017). Our study differs from these meta-analyses in several important ways. One of the key differences is that this study used a larger and more contemporary body of literature, thus lending strong credibility to our findings. Unlike existing meta-analysis studies that have used predictors derived mainly from TAM as their theoretical underpinning, our study included other important theories such as UTAUT. In our application of TAM/UTAUT, we also examined different versions such as TAM2 (i.e., image, output quality), TAM3 (i.e., result demonstrability, self-efficacy), and UTAUT2 (i.e., value, enjoyment). Therefore, we can offer more theoretical insights into the predictors of HIT adoption. Chauhan and Jaiswal's (2017) study focused on the predictors of HIT but excluded contextual moderators. Furthermore, their model focused on using TAM instead of UTAUT and stated in their recommendation for future study to "focus on some of these state-of-the-art theories (e.g., UTAUT) in the field of e-health applications acceptance" (p. 311).

Although Tao et al. (2020) examined the role of contextual factors that influence HIT adoption, our study's proposed contextual moderators differ from their study. Although their paper stated that part of their results was consistent with UTAUT, they did not examine the moderators in UTAUT, which are age, experience, and gender. They focused on consumer use of HIT, whereas this study aimed to be comprehensive by examining adoption from both the patient and the non-patient (doctors and nurses) perspectives. Furthermore, Tao et al. (2020) focused on Asian versus non-Asian users.

Nevertheless, classifying users broadly into Asian versus Western users may not provide accurate insights into user characteristics as countries within these two contexts may vary significantly. Thus, instead of treating users as Western versus Asian, we have examined whether contextual factors related to a country's healthcare system would influence users' decisions to adopt HIT. These contextual factors align with Venkatesh et al.'s (2016) recommendations to consider context-related variables in models such as UTAUT. Lastly, our study examined the relative importance of predictors in a structural equation model (SEM). Previous meta-analyses by Tao et al. (2020) and Chauhan and Jaiswal (2017) did not employ structural equation modeling. However, the authors specifically recommend this method in their future research section: "Future studies are suggested to examine TAM relationships in a holistic way with methods such as meta-analytic SEM to obtain a more precise estimation of the relationships among TAM variables (Cheung & Chan, 2005) when data on all the relationships examined are available" (p. 9). This is addressed in our study. We also tested the importance of context moderators while controlling for the impact of other contextual factors by using random-effects meta-regression. This approach differs from previous HIT meta-analysis studies, which only assessed each moderator's effect in isolation. On the other hand, our approach allowed controlling for the influence of various study characteristics. A summary of the difference between our study and the existing HIT meta-analysis studies is shown in Table 1.

[Table 1 about here]

The remainder of the paper is structured as follows. The following section gives a brief overview of different theories employed to explain technology acceptance, and the moderators examined in current HIT studies. Following this, we discuss the conceptual framework of our research and derive the hypotheses. After presenting the method and results of our meta-analysis, we discuss the key findings and implications for research and practice.

LITERATURE REVIEW

Healthcare Information Technologies

The term HIT refers to information technologies that are applied to health and healthcare. They involve the application and exchange of information electronically in a healthcare environment such as in hospitals and clinics. They often include computer hardware and software technologies, which deal with the storage, retrieval, sharing, and use of healthcare information, data, and knowledge for communication and decision-making (Thompson and Brailer, 2004). This information includes the patients' EMRs, electronic health records (EHR), drugs and equipment inventories, hospital bedroom scheduling information, doctors and nurses' working timetables, and so forth, which are exchanged with the help of HIT (Chong et al., 2015).

Successful HIT implementations can have several benefits such as improvement in healthcare quality delivery, improvement in delivery efficiency, prevention of medical errors, reduction of administrative workloads, reduction of healthcare costs, and improvement of communication between healthcare professionals and their patients (Chong et al., 2015). Despite the numerous benefits promised by HIT, there are many challenges in implementing it in the healthcare industry. One of the key challenges is the low adoption rate of HIT, which can be attributed to various reasons such as the technology resistance of healthcare workers (Bhattacherjee and Hikmet, 2007), the experience of the healthcare professionals in using technologies (Kijsanayotin et al., 2009), and the characteristics of the technology (e.g., privacy issues, data integration) (Kohli and Tan, 2016). Given that the healthcare industry is one of the most important industries to most nations in terms of GDP and investments, understanding the successful acceptance and use of HIT is critical for the long-term success and growth of the industry.

Technology Acceptance Theories

Research on the acceptance of healthcare technologies is a growing stream in the IS literature. Two key theories that have been applied extensively by existing studies are TAM and UTAUT. These models are also two of the theories most widely cited by researchers studying technology acceptance. The TAM posits that the perceived ease of use and usefulness of a technology will influence an individual's intention to use it. The intention to use will also serve as a mediator to the actual use of the technology. Perceived ease of use will also influence the perceived usefulness of the system. The original TAM was extended into TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008). In TAM2, Venkatesh and Davis stated that it is important to understand the determinants of perceived usefulness and included social influence processes, such as subjective norm and image, and system characteristics, such as task relevance, output quality, and result demonstrability, and perceived ease of use and voluntariness. In TAM3, Venkatesh and Bala (2008) proposed the determinants of perceived ease of use such as computer self-efficacy, perceived enjoyment, and computer anxiety, to name a few.[1]

The UTAUT model was developed after TAM and was proposed as a unified model based on eight theories, including TAM (Venkatesh et al., 2003). It proposed four main constructs that can influence the acceptance and use of technologies: performance expectancy, effort expectancy, social influence, and facilitating conditions. Several of the TAM constructs are also discussed in UTAUT under different labels. For example, performance expectancy is similar to usefulness in TAM, and effort expectancy is similar to ease of use (see Table 2 for construct definitions and aliases).[2] The UTAUT model also proposed four key moderators: user age, gender, experience, and voluntariness of the technology use. Similar to TAM, UTAUT was also further developed and extended by various researchers. Venkatesh and his colleagues in 2012 also developed UTAUT, which examined non-organizational technologies and included variables such as hedonic motivation and habit and price as predictors of technology acceptance and use.

Despite TAM and UTAUT being examined extensively in HIT, many studies have examined different sets of determinants to extend them in HIT studies. Because the various studies provide inconclusive results on the importance of specific factors, it is difficult for practitioners to formulate HIT implementation strategies based on these findings. It is critical to examine existing studies on HIT acceptance and develop a single, unified theory of HIT, which integrates the most important determinants from different studies, to help practitioners and researchers understand how HIT can be implemented successfully in the healthcare industry.

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[1] The present study uses the term TAM when referring to TAM and also subsequent versions of TAM such as TAM2 and TAM3.
[2] The present study uses the UTAUT terminology when referring to constructs discussed in both theories.

Mediating Effects in Technology Acceptance Studies

The technology acceptance model assumes that external variables predict the usage of a system through their effects on perceived ease of use and perceived usefulness (Davis, 1989). It also suggests that the impact of external variables on behavioral intention is mediated by perceived usefulness and perceived ease of use. The model has been tested extensively, and the mediating effects of both perceived ease of use and perceived usefulness were confirmed by various studies such as those by Venkatesh (2000), Wang (2020), and Tsai et al. (2019). Despite the assumption and subsequent confirmation of the mediating roles of perceived ease of use and perceived usefulness, many TAM studies have not tested such mediation effects. For example, the meta-analyses of HIT acceptance by Tao et al. (2020) and Chauhan and Jaiswal (2017) did not examine the mediating roles of perceived ease of use and perceived usefulness on external variables and HIT behavioral intention. One of the reasons why technology acceptance scholars have yielded inconsistent findings could be attributed to not sufficiently and suitably replicating the full, original model, including the moderating and mediating relationships in their studies, an issue that is of great importance to scientists (Dennis and Valacich, 2014; Tsang and Kwan, 1999; Venkatesh et al., 2016).

Besides perceived ease of use and perceived usefulness, which focus on the affective aspect of attitude, Davis et al. (1989) found that the influence of attitude on IS use was at best modest in predicting the intention to use IS. They found that the influence of attitude on IS use disappeared when perceived usefulness was considered to predict IS use. Therefore, they believed that this attitude offers little value in predicting IS use, making the two user beliefs—perceived usefulness and perceived ease of use—powerful and parsimonious predictors of IS use. However, social psychology literature suggests that attitude has both affective and cognitive components, thus challenging Davis et al.'s (1989) argument on the limited effect of attitude. As argued by Yang and Yoo (2004), although the underlying theory used by Davis et al. (1989) "assumed no cognitive component of attitude, the indicators for the attitude construct they used included both the cognitive and affective aspects" (p. 20). Second, provided that attitude has both cognitive and affective aspects, whether both aspects of attitudes mediate the impact of perceived usefulness and perceived ease of use on IS use should be examined. Yang and Yoo (2004) recommended that attitude deserves careful attention in IS studies. It has powerful potential to influence the implementation of technology and the diffusion of IT-enabled innovation in organizations. Based on these discussions, to fully replicate the full TAM model, our study proposed perceived ease of use, usefulness, and attitude as mediators of external factors and HIT usage intention and usage behaviors.

Moderators in Technology Acceptance to Examine Contextual Factors in HIT Acceptance

In technology acceptance studies, researchers have frequently proposed moderators that can influence the importance of acceptance determinants. In the TAM3 model, Venkatesh and Bala (2008) suggested both the user's experience and the voluntariness of using the technology to be important moderators. The authors found, for example, that experience moderated the effect of ease of use and usefulness such that the effects become stronger where there is an increase in experience. They also found that experience moderated the effect of computer anxiety on perceived ease of use, causing the effect to become weaker with increasing experience. The UTAUT model also proposed important moderators such as the age, gender, experience, and voluntariness of those using the technology (Venkatesh et al., 2003). One of the key challenges faced by technology acceptance theories such as UTAUT is that they have not been fully replicated nor has the boundary of the theory been examined. This frequently results in inconsistent findings when applying the theory to similar technology studies (Venkatesh et al., 2016).

Moderators are important as they provide us with an understanding of the contextual role of the technologies studied. We used Johns (2006) and Venkatesh et al.'s (2016) conceptualization of the dimensions of research contexts as a guideline to select the contextual moderators in this meta-analysis study. Since HIT differs from other technologies, there is a need to extend existing theory by postulating the impact of different healthcare contexts and healthcare technologies. Hong et al. (2014) defined the IS research context as the characteristics and usage contexts of the IS artifact and provided recommendations for contextualizing IS research. Despite the important roles of moderators and contextual factors, many technology acceptance studies have often excluded healthcare-related moderators in their research (Venkatesh et al., 2016). Johns (2006) and Venkatesh et al. (2016) identified several dimensions of the context of technology acceptance. Venkatesh et al. (2016) referred to these dimensions as the users of the technology, location, and IT artifact. We adapted three specific contextual moderators that are relevant for HIT technology acceptance studies. In this meta-analysis, we proposed three groups of important moderators that can help to understand the acceptance of HIT in the healthcare industry: (1) technology characteristics, (2) user characteristics, and (3) location characteristics.

Technology characteristics in our study refers to the type of target technology being adopted in the healthcare industry. Although there is no standard approach to classify different categories of HIT broadly, we applied the principles from previous studies such as those by Meuter et al. (2000) and Rich and Miah (2017) to classify the HIT studied. While research by Furukawa et al. (2008) classified HIT into prescribing and dispensing medications, taking such an approach would result in our study examining the issues from the perspectives of healthcare professionals' behavioral intention and use of HIT, instead of a broader view from general users and patients. Rich and Miah (2017) stated that wearable and mobile healthcare devices are radically changing how healthcare services are being provided. Mobile and Internet technologies allow users to have access to ubiquitous healthcare services anytime, anywhere. Therefore, this study classified HIT from the perspective of wearable and mobile HIT and classified existing HIT studies guided by Meuter et al.'s (2000) study, which investigated technology's main purpose and interface. This classification was applied by Meuter et al. (2000) to examine the different expectations of users.

Existing HIT studies included in this meta-analysis have their theoretical underpinnings based on TAM and UTAUT. However, these theories were developed before the age of the Internet and mobile technologies. The UTAUT2 model (Venkatesh et al., 2012) was developed to include predictors relevant to consumer technology (i.e., habit, hedonic motivation, and price value). In summary, the technology characteristics in this study are based on the determination of whether a particular type of HIT is based on remote versus non-remote technologies (main purpose) or wearable versus non-wearable technologies (interface). Remote technologies allow users to have access to medical services without physically attending the hospitals or clinics. These can improve patients' accessibility to healthcare and reduce their healthcare delivery costs. Wearable technologies are electronic devices that can be worn directly on the body (Gao et al., 2015), and they can be used for different healthcare purposes. Wearable devices allow users to immediately monitor their fitness condition, such as the number of steps, amount of sleep, and diet. Examples of such devices include Fitbit and Apple Watch. Other wearable devices can be used to monitor conditions, examples being current blood sugar levels or the speech and voice disorders of patients with Parkinson's disease (Dubey et al., 2015). As Gao et al. (2015) demonstrated in their study, users' intentions to adopt and use remote and wearable HIT are different from those with non-wearable HIT due to different concerns related to security and privacy of the data.

The conceptualization of *user group* extends studies by Goodhue and Thompson (1995), Johns (2006), and Venkatesh et al. (2016) to include users who do not fit into the organizational boundary. Venkatesh et al. (2016) stated that technology acceptance theories such as UTAUT's user attributes could include user types, occupation, and demographics. Johns (2006) defined user class based on the occupational and demographic context. Weber (2012) focused on the individual users who use the technology to help them to perform their tasks. Venkatesh et al. (2003) also suggested that to examine the boundary conditions of UTAUT, researchers should consider examining additional theoretically motivated moderating influences such as different user groups. Building upon John (2006) and Weber's (2012) suggestions, in this meta-analysis, we examined differences across users depending on their specific user *characteristics,* including user group, the voluntariness of using the technologies, and user experience. There are two key groups of users for HIT: the patients and the healthcare professionals such as doctors and nurses. Prior studies such as those by Venkatesh et al. (2011) and Chong et al. (2015) found distinct differences in the motivations of different healthcare professionals or users in accepting HIT. Given that the purpose of using HIT for patients and healthcare professionals is different, different factors could influence their intentions to use and adopt it. For example, from the healthcare professional's perspective, the factors influencing their decisions to use EMR can be related to their job performance (Sykes et al., 2011), whereas from the patient's perspective, it could be related to the privacy of their data (Kohli and Tan, 2016). Successful implementations of HIT require its acceptance and use by the two groups of users. Therefore, it is crucial to understand the antecedents driving the behavioral intention and use of HIT by examining the moderating effects of the user group, namely patients and healthcare workers.

Despite being part of UTAUT, many technology acceptance studies have continued to omit demographic factors such as age, voluntariness, and experience as moderators (Venkatesh et al., 2016). However, these demographic factors play an important role in influencing the predictors of technology acceptance theories such as UTAUT. For example, in Venkatesh et al.'s (2011) study of doctors' use of EMR, age plays a key moderating role in determining UTAUT predictors. When examining voluntary or mandatory settings of technology use in organizations, the original UTAUT found that social influence does not play an important role in an organizational setting where the use of the technology is made mandatory. Nevertheless, scholars have also argued that individuals are more likely to comply with other expectations when the referent others can reward or punish the behavior/inaction. Thus, reliance on others' opinions could only be important in a mandatory setting rather than a voluntary setting. Similarly, age is a key moderator in UTAUT, and job-attitude-related research has found that younger workers are more likely to be influenced by extrinsic rewards and, hence, more likely to impact user performance expectancy. Other age-related studies show that older users may also face greater difficulties in processing complex stimuli and allocating attention to the job information (Cimperman et al., 2016). Thus, doctors with extensive clinical experience may find it more difficult to use newer technologies than younger doctors. The above discussions show that by only examining the main effects from models such as TAM and UTAUT, we would not examine the generalizability of acceptance theories when applying them to HIT and the healthcare setting.

Furthermore, many technology acceptance studies such as TAM, the innovation diffusion model, and the theory of planned behavior have been conducted in voluntary usage contexts, thus reducing our understanding of how users accept HIT in healthcare organizations, which have a more mandatory setting for using HIT (Venkatesh et al., 2003). In terms of experience, most literature has found that users with previous IT experience are more likely to use HIT (Kijsanayotin et al., 2009). For example, the effect of effort expectancy on behavioral intention is stronger for users who have less experience. Venkatesh et al. (2003) found that in UTAUT age has several moderating effects on the model's predictors. Facilitating conditions' influence on usage is stronger for older workers with more experience. However, how experience moderates important antecedents of technology acceptance in the healthcare industry remains to be studied as there are some inconsistent results, such as in the study by Venkatesh et al. (2011) who found that experience played no significant moderating roles in doctors' use of EMR systems (Venkatesh et al., 2016).

Lastly, we also adopted Weber's (2012) conceptualization of location class as a moderator in our study. Venkatesh et al. (2016) proposed that the *location* of the study is an important area for extending acceptance theories such as UTAUT. Location is defined as the place where the target technology is introduced, implemented, adopted, and used. The study location can be characterized by national culture, the region's economic status, and industry competition. In this meta-analysis, we have included location as a moderator influencing HIT behavioral intention and use. The selection of our HIT-related locations are variables related to whether the setting of the studies was in hospitals or other locales (i.e., smaller clinics, homes of patients), the quality of the country's healthcare system where the HIT was accepted or implemented, and the life expectancy in the country where the studies were conducted. In previous meta-analyses of HIT, such as the study conducted by Tao et al. (2020), the study's location refers to the research site's world region. However, our focus was on the quality of care in different countries, a key metric for healthcare providers (Venkatesh et al., 2011). However, given that our study was not able to examine the individual user's assessment of the quality of the healthcare provided, we have adopted an examination of a broader, macro-environmental location factor relevant to HIT.

Regarding the in-hospital versus out-of-hospital settings, the key difference could be the resources available, for example, technical and financial supports. As HIT should be broadly implemented in the healthcare industry to be successful, and not just in large hospitals, this meta-analysis examined the differences in technology acceptance for these two types of settings. Similarly, we aimed to examine whether a country's healthcare quality influences the acceptance drivers. We measured the quality of a country's healthcare system by examining two attributes: the quality of the health system's index and the country's life expectancy. These two attributes were selected after careful examination of the healthcare index based on NUMBEO, which considers the quality of healthcare professionals, equipment, staff, doctors, and costs, among others. The life expectancy of a country was based on data provided by the OECD, which is frequently used as a health status indicator.

While some of the proposed moderators received some attention in the technology acceptance literature, such as age and experience of the user and voluntariness of usage, other moderators received less or no attention. In particular, those moderators that compare different technologies by country are usually difficult to test in primary studies. While the literature gives some indication that country and technology differences exist, they are rarely tested. Meta-analyses combine data from various technologies and countries, allowing them to test these novel moderators and contribute to theory.

CONCEPTUAL FRAMEWORK AND HYPOTHESES

The conceptual framework of this meta-analysis is presented in Figure 1. We proposed that various acceptance predictors are related to the usage intention and usage behavior toward healthcare technologies. Since TAM proposes ease of use (effort expectancy) and usefulness (performance expectancy) as mediators (while UTAUT does not), we also tested the mediating effects of these constructs and considered attitude toward using a technology (Davis et al., 1989). Since the main effects of this model were discussed in major acceptance theories, we only derived hypotheses for the moderating effects. We examined variables related to the type of technology, the user, and the location of the study as moderators.

[Figure 1 about here]

Types of Healthcare Technologies

Remote technologies. The acceptance predictors discussed vary in importance depending on the technology being studied (Im et al., 2008). In our study, we differentiated between remote HIT and non-remote technologies. Remote technologies are sometimes also referred to as telemedicine in the literature. Remote HIT uses IT such as the Internet and mobile technologies to provide clinical healthcare from a distance. It can help to address challenges related to access to healthcare while at the same time being cost-effective to healthcare providers and patients (Chau and Hu, 2002). In a recent study, Blut et al. (2021) found that mobile technologies have changed the ways in which users interact with new technologies. Their research, which was based on a meta-analysis of UTAUT studies, found that as mobile technologies changed the way people conduct work, they tended to find that the performance expectancy, effort expectancy, and facilitating conditions were important moderators for technology acceptance compared to those of other technology (non-mobile technologies). Building on their argument, most patients are more familiar with visiting hospitals or clinics to seek medical treatments. However, the concept of telemedicine is relatively new to most people (Jansen-Kosterink et al., 2019). As such, most users who would like to use telemedicine will need to learn the technology and, therefore, effort expectancy will be important for the acceptance of remote technologies.

Furthermore, users also need to believe that remote technologies offer better value when compared with the traditional approach of having patients physically visit a hospital or clinic. Although remote services offer convenience, as users may not need to travel, they need to learn how to set up and use the telemedicine system. This is supported by Rho et al. (2015), who found strong support for effort expectancy, facilitating conditions, and users' behavioral intention to use technology in their study with regard to the use of telemedicine for diabetes management. Empirical studies indicate that the importance of acceptance predictors such as effort expectancy, facilitating conditions, and self-efficacy vary across technologies. Most of these studies were conducted in the context of e-commerce and leisure-related applications instead of HIT (Chong et al., 2012; Zhou et al., 2010). There is no reason to argue that these factors would not also apply to remote technologies that would be new to users when applied to telemedicine. Against this background, effort expectancy, self-efficacy, and facilitating conditions are proposed to have stronger effects on remote technologies. Whether users are medical workers, such as physicians and nurses, or patients, they would require some training and support to use the system. Hence, facilitating conditions play an important role as well (Ryo et al., 2015).

Nevertheless, users with higher self-efficacy are more likely to adopt remote technologies (Rho et al., 2014). This is supported by previous studies that stated that despite physicians being considered as healthcare experts, many of them reported a lack of confidence in using new technology for clinical practice (Rho et al., 2014). However, physicians with higher self-efficacy for devices and telemedicine services have demonstrated a more proactive attitude for acceptance. Therefore, the following hypothesis was proposed:

H1: (a) Value displays, (b) effort expectancy, (c) facilitating conditions, and (d) self-efficacy all display a stronger effect for remote technologies.

Wearable technologies. Wearable technologies in healthcare are increasingly popular and are used as either a fitness wearable device such as Fitbit or a medical wearable device that monitors a user's conditions such as diabetes (Gao et al., 2015). Unlike many HIT, wearable devices are worn by users. As many of them require financial investment by the users, they need to be convinced of the quality, usefulness, and value of the wearable devices (Yang et al., 2016). In terms of quality, consumers have a higher behavioral intention to use wearable devices if they can observe quality-related attributes such as comfort, battery duration, and functional congruence (Gao et al., 2015). The study by Hong et al. (2017) also found that users are more likely to use wearable devices if the perceived values and performance expectancies are high. However, their study focused on smartwatches rather than wearable devices related to healthcare.

It should be noted that most of these devices are designed to be quite user-friendly. Therefore, traditional technology acceptance factors such as effort expectancy and self-efficacy may not be the most important predictors for wearable technologies. Instead, given that users wear the devices to control their bodies, the quality and outcome of the wearable devices may play an essential role in the users' adoption decisions (Gao et al., 2015). Yang et al. (2016) stated that wearable devices are currently a trend among users, and wearable device users can be considered innovators due to their early adoption. Therefore, social influence also plays an important role in the users' adoption decisions. Nevertheless, given that these devices are not compulsory for users, most will only invest in the technology if they find that the product offers good value for their money. Therefore, we hypothesized that:

H2: While (a) output quality, (b) performance expectancy, and (c) value display stronger effects for wearable technologies, (d) effort expectancy and (e) self-efficacy display weaker effects.

User Characteristics

Staff versus patient. HIT can be used by both medical professionals and by the patients themselves. However, in most HIT acceptance research, there have rarely been any studies contrasting these two groups of users. In UTAUT studies, most researchers have examined the differences in technology adoption decisions between employees and consumers. These studies tended to find that the constructs that predict behavioral intention and use vary across these categories. The UTAUT predictors tended to show strong effects for consumers (Thong et al., 2011; Powell et al., 2012) and less for employees. For HIT use, HIT in general are related to medical staff, while consumers are related to patients. Some studies have indicated that patients and doctors' views on HIT differ from each other (Miller, 2016). It is important to distinguish between these two groups, as they are likely to have different motivations to use HIT. This is critical to implementing HIT as both users and healthcare workers need to co-adopt the technology to ensure the eventual success of its diffusion. Furthermore, previous HIT studies such as EHR have tended to examine adoption issues from organizations' perspectives.

Limited studies have focused on individual levels such as doctors, para-professionals, and healthcare administrators (Chong et al., 2015). When they do, there are no differentiations between healthcare staff and the patients. While staff use HIT as part of their job to fulfill their role, patient treatment and technology use are more personal for the recipient (Kohnke et al., 2014). Healthcare staff are usually more experienced regarding diseases, treatments, and technologies since they have worked in their profession for many years, whereas most patients receive only occasional health treatment. With greater expertise one can assume that the staff using HIT are more influenced by technology attributes and assess technology more rationally (Mun et al., 2006). In contrast, patients are led by issues related to emotions, anxieties, and norms and may have problems assessing the technology (Or and Karsh, 2009). Therefore, it was proposed that patients are more affected by technology anxiety, norms of technology use, facilitating conditions, and self-efficacy. Patients lacking the expertise to assess technologies may have the feeling of low self-efficacy and require support in using the technology. Staff are more aware of the technology; therefore, to make the performance of technology more important, it has to be easy to use to suit the routines in their job. The value is more important since they are encouraged to care about cost-efficiency. Venkatesh et al. (2012) further argued that predictors such as habit and enjoyment in UTAUT2 are less relevant for organizational contexts where staff use technology. This was also further confirmed in a more recent paper on UTAUT by Blut et al.

(2021) where habit and enjoyment were found to be more relevant for users in non-organizational use contexts. Thus, we hypothesized:

H3: (a) Performance expectancy, (b) effort expectancy, (c) value display, (d) technology anxiety, (e) norms, (f) facilitating conditions, (g) self-efficacy, (h) habit, and (i) enjoyment will have different effects for staff and patients.

User age. Previous studies of technology acceptance have examined socio-demographic variables as moderators. While UTAUT proposes age as a key moderator, later studies often did not test these user characteristics or failed to provide evidence for the moderating effect. The UTAUT2 model also proposed age as an important moderator for predictors such as effort expectancy and facilitating conditions (Venkatesh et al., 2012). It is usually argued that a person's capability to process information declines with age (Gilly and Zeithaml, 1985). John and Cole (1986) pointed out that by adulthood, individuals typically have a well-developed information processing system that includes a full repertoire of mnemonic strategies and an extensive knowledge base. As individuals get older, the processing system slows down, becomes less efficient, and their access to and use of their knowledge appears to break down. Blut et al. (2016) suggested that older individuals are more likely to experience difficulties in processing new information, which may affect their ability to familiarize themselves with new technologies. Therefore, older users are assumed to require more support in adopting new technology use (facilitating conditions) and find HIT difficult to use (effort expectancy). Another moderator of age that previous studies have examined is self-efficacy. This is the core of social cognitive theory. When applied to research technology adoptions by older users, researchers such as Lam and Lee (2006) and Tsai et al. (2015) defined it as a user's belief in their skills in using the technology. Self-efficacy can better explain the adoption of technologies such as the Internet or tablets for older users (Lam and Lee, 2006; Tsai et al., 2015). We believed this would extend to HIT adoption for older users with higher self-efficacy. Thus, we hypothesized:

H4: With increasing user age, the effects of (a) facilitating conditions, (b) effort expectancy, and (c) self-efficacy become stronger.

Voluntariness of usage. The moderating effects of the voluntariness of using technology have been examined in previous acceptance studies (Hennington and Janz, 2007; Kijsanayotin et al., 2009) and models such as TAM and UTAUT (Venkatesh et al., 2003; Wu and Lederer, 2009). Therefore, it is possible that the users' acceptance decisions in the HIT context also depend on whether the work environment makes technology use compulsory. On the other hand, Venkatesh et al. (2011), in their study on EMR adoption, found that voluntariness does not play a significant moderating role in influencing factors derived from UTAUT (i.e., performance expectancy and effort expectancy). Some of the reasons why voluntariness has inconsistent results could be due to the context of the technologies, such as whether it is an organizational or consumer technology. For example, consumers have no organizational mandate and most of their behaviors are completely voluntary (Blut et al., 2021).

We proposed, in our study, that in the case of voluntary use, users can decide whether and when to use the technology. Users being forced to learn the technology are more likely to familiarize themselves with it, making ease of technology use and self-efficacy less relevant as predictors. In contrast, performance expectancy and output quality are more important for involuntary technology use. Users being forced to use technology are more likely to assess technologies more critically and their performance expectancy, whereas voluntary users are less critical. Thus, we hypothesized:

H5: While (a) effort expectancy and (b) self-efficacy display <u>stronger</u> effects for <u>voluntary users</u>, (c) performance expectancy and (d) output quality display <u>weaker</u> effects.

Usage experience. The experience of the users may also impact the importance of various predictors. Usage experience is one of the key moderators in UTAUT (Venkatesh et al., 2003). However, it is not always included in replication studies that apply the theory (Venkatesh et al., 2016). Experience has been examined in UTAUT and found to moderate predictors such as effort expectancy and facilitating conditions. As predicted by UTAUT, more experienced users, in general, would tend to be less influenced by the effort expectancy and facilitating conditions when using new technologies (Al-Gahtani et al., 2007). The characteristic of experience as a user has been examined before in general IS literature and in the context of healthcare adoption (Kijsanayotin et al., 2009). Blut et al. (2021) also found that users' experiences with technologies are transferable without difficulty to a specific technology, thus making the user adjustment effect relatively strong. It is usually argued that more experienced individuals display more well-developed mental structures (Alba and Hutchinson, 1987). These structures help the user to encode and retrieve the information needed to evaluate new technologies more easily and facilitate learning (Alba and Hutchinson, 1987). Therefore, it is reasonable to believe that users with significant experience, compared with inexperienced users, display fewer anxieties associated with technology use. They also find the technology to be more useful and appreciate the value of their expense. Without the necessary experience, users would struggle to assess the benefits of the technology, have difficulties assessing its task relevance, and assess the price value more critically. Lacking the necessary experience, inexperienced users are more likely to rely on more accessible cues to assess their use decision, such as the anticipated image gain associated with technology use and result demonstrability. Hence, we hypothesized:

H6: While (a) performance expectancy, (b) output quality, (c) value, and (d) task relevance display stronger effects for experienced users, (e) technology anxiety, (f) effort expectancy, (g) facilitating conditions, (h) result demonstrability, and (i) image display weaker effects.

Location Characteristics

Hospitals versus non-hospital settings. As Blut et al. (2021) stated, contextual differences between where the technologies are implemented could provide a new theoretical specification in the study of technology adoptions. Al-Gahtani et al. (2007) found that location differences play an important role in using IT. Blut et al. (2021), in their meta-analysis of UTAUT, stated that one of the reasons why adoption decisions can be influenced by location could be attributed to the cultural differences of the locations. Most studies tend to employ the Hofstede model and examine cultural differences such as the countries' power distance and collectivism, to name a few. In this study, we proposed that the location where an IS is implemented or introduced may play a role in whether it is adopted successfully or not (Venkatesh et al., 2016). Instead of looking at location in the context of countries where HIT is being implemented, we defined the location as the usage of HIT in a hospital or a non-hospital setting. As hospitals have more extensive operations, better facilities, and resources, they can likely provide better support for HIT usage. Some smaller non-hospital healthcare providers also have less financial resources to invest in HIT (Baker, 2001). As the quality of facilitating conditions varies more in less professional settings, it is likely that facilitating conditions matter more in non-hospital settings. Due to their size, facilitating conditions, and professionals working in the hospital environment, it is more likely that hospitals generally ensure better output quality from implementing HIT (Zhang et al., 2013). Output quality varies more for non-hospital settings due to the lower professionalism and fewer processes; thus, output quality is a stronger predictor for non-hospital settings. While hospitals' size and professionalism help implement technologies, an increase in size is also related to greater user anonymity and lower process transparency. Users in these settings are more likely to experience anxieties regarding using the latest technologies with their anonymity. In smaller healthcare organizations, where the individual user is less anonymous, HIT users are less likely to suffer from these anxieties.

H7: While (a) technology anxiety displays <u>stronger</u> effects for in-<u>hospital</u> settings, (b) facilitating conditions and (c) output quality display <u>weaker</u> effects.

Quality of country's healthcare system. Many technology acceptance studies have found that users from countries with different levels of economic development display different behavioral patterns in adopting new technologies (Straub et al., 1997). Our meta-analysis examined whether there was a difference in the decisions to adopt HIT in countries with better quality healthcare systems and higher life expectancy. Previous studies have compared HIT adoption in different countries. Most of these studies have examined this from a cultural perspective (Huang et al., 2010) or compared developed versus less-developed countries (Sood et al., 2008). However, simply because a country is a developing country does not necessarily mean it has a good healthcare system. Thus, our study examined country differences with more differentiated criteria. In the World Health Organization's ranking of health systems worldwide, developing countries such as Malta, Oman, and Colombia are ranked higher than developed countries such as Germany, Canada, and the United States (WHO, 2017). Thus, it could be argued that the country's quality of healthcare system impacts the acceptance of new technologies instead of its developmental status (Lucas, 2008).

Similarly, in the current COVID-19 pandemic, countries with better healthcare systems can invest in better IT technologies to support their citizens. However, in the case of a tracing app, examining a country's economic development status may not necessarily provide a clear picture of its citizens' willingness to adopt the technology. Rowe et al. (2020) found that French citizens were unwilling to adopt tracing apps due to privacy and unclear government policy. Similarly, Japan, an economically developed country with strong healthcare systems, has a very low rate of tracing app adoption by its citizens (Statista.com, 2021).

In general, in countries with better healthcare systems (e.g., higher life expectancy), users are expected to show fewer anxieties when using HIT since they are reassured that they will receive the best treatment possible. In contrast, anxieties are expected to be stronger in countries with poor healthcare systems (e.g., lower life expectancy). Nonetheless, professional health treatment often requires users to be involved in their treatment to a greater extent and use more technologies (Vita Wave Consulting Report, 2009). Thus, self-efficacy gains importance in these countries. Also, professional healthcare is quite costly, and users may be more worried about the value of HIT than in less professional countries. Notably, patients in the US often worry about the costs of treatment because of the comprehensive nature of treatment available. Hence, we developed the following hypothesis:

H8: With increasing healthcare quality (life expectancy) in a country, the effects of (a) self-efficacy and (b) value display stronger effects, whereas (c) technology anxiety displays weaker effects.

METHOD

Search Strategy and Study Coding

This study was conducted in accordance with the approaches of Tao et al. (2020) and Higgins et al. (2019). A systematic literature search was conducted of databases including ABI/INFORM global, Business Source Premier, ProQuest, Science Direct, Scopus, and Web of Science to identify empirical studies testing the acceptance of healthcare technologies. To reduce the likelihood of missing relevant studies, we used broad search terms that included keywords and associated controlled vocabularies. Specifically, the search strategy included combinations of two sets of terms related to healthcare (e.g., health, healthcare, eHealth, mHealth, telehealth) and technology adoption (e.g., technology adoption, technology acceptance, TAM, UTAUT).

After the initial search, we first screened the titles and abstracts of articles and deleted those that were not relevant to our study. Next, the full texts of potentially relevant studies were reviewed for final inclusion in the meta-analysis. Four criteria were adopted to determine their suitability. First, the studies must have empirically tested the relationships between antecedent factors and healthcare technology adoption (e.g., using survey, experiment, or both). Second, the studies must report correlation coefficients or other statistical information that can be used to calculate correlations. Third, the studies had to report on an independent data set to avoid the same data set being used twice in our meta-analysis. Fourth, the studies were written in English. Figure 2 illustrates the process of the literature search and study filtering. In total, 193 studies were found to be relevant to the area of HIT adoption. A complete list of the articles identified is provided in Web Appendix B.

A coding strategy was developed to provide guidance for data extraction from the selected studies (Jeyaraj and Dwivedi, 2020). Specifically, the filtered articles were scanned again for those that had certain variables and constructs were utilized to analyze the adoption of HIT. We focused only on empirical studies and used correlations as primary measures of effect size for this meta-analysis. The correlation coefficient was scale free and not influenced by other variables. If correlation coefficients were not available, we coded information that could be used to calculate the correlation coefficients (e.g., standardized regression coefficients, *t*-values, means, and *SD*s). For example, some primary studies reported standardized beta coefficients, and we used the conversion formula suggested by Peterson and Brown (2005).[3] Among 193 studies, 145 studies reported the correlation results among constructs, and 48 studies that applied regression methods merely reported the regression results without correlation. Thus, we divided these studies into two groups and coded both the correlation and standardized regression coefficients, respectively.

The general information about the studies (e.g., research context, ground acceptance theories, technology type, the country where the study was conducted) were coded for further positioning. For example, we divided the studies into in-hospital and non-hospital settings based on their research context description. Similarly, we distinguished the studies that focused on wearable technology and remote technology from the whole data set according to the technology type reported. In addition, the demographics of the respondents (gender ratios, mean age, participant type, and sample size) were also coded. While most of the variables were unambiguously labeled in the studies, the coders also identified the sample's voluntariness and prior experience with the technology based on the description found in each study. These two constructs were coded as dummy variables.

To verify the accuracy of the coding effort, two independent researchers coded the studies and resolved inconsistencies in coding by discussing differences (agreement rate > 95%). When coding the studies, the coders used the construct definitions provided in Table 2. When articles reported more than one correlation for a specific relationship, for instance, between effort expectancy and usage intention, we averaged these correlations to ensure that the article did not receive disproportionate weight in subsequent analyses. The final data set included 3,020 correlations reported in 214 independent samples, extracted from the 193 articles. The cumulative sample sizes in our study are 83,619 users from 33 different countries worldwide.

[Figure 2 and Table 2 about here]

Effect Size Integration

[3] We assessed whether the study results differed when differentiating between correlation coefficients and converted correlation coefficients by including the calculation method as moderator (Table 6). In total, 83 of 86 moderator tests remained the same.

The meta-analysis followed the procedures suggested by Hunter and Schmidt (2004). This meta-analytic approach is a random-effects approach, which suggests correcting the effect sizes for measurement error before averaging them. We, therefore, divided each correlation by the product of the square root of the respective reliabilities of the two constructs. In cases where studies did not report reliabilities, we replaced the missing reliability with the average reliability across the collected studies. We then weighted each reliability-adjusted correlation by sample size to adjust for sampling error. We also calculated 95% confidence intervals for each sample size-weighted and reliability-adjusted correlation and the 80% credibility intervals. The credibility interval describes the distribution of effect sizes, and larger intervals suggest the extent to which moderators might account for the unexplained variance (Whitener, 1990). We tested publication bias by calculating the classic file-drawer analysis suggested, which is also referred to as fail-safe N (FSN; Rosenthal 1979). The FSN refers to the number of studies averaging null results necessary to lower a significant relationship to a barely significant level ($p=.05$). According to Rosenthal (1979), results are robust when FSNs are greater than $5 \times k + 10$, where k=number of correlations. Finally, we assessed the homogeneity of effect size distribution using the Q test, which assesses the between-study variability in the population effect size estimated by the individual studies. The Q statistic has a chi-square distribution with $k - 1$ degrees of freedom (k=number of studies).

Structural Equation Model

To assess the mediating effects in our conceptual model, we employed SEM. Therefore, a correlation matrix was produced for the most-often reported constructs in prior research. These correlations were taken as inputs to LISREL 9.2 to calculate the SEM. This analysis uses the harmonic mean of all effect sizes in the correlation matrix. The harmonic mean produces more conservative results than the simple mean, and it is therefore frequently employed in meta-analyses.

Moderator Analysis

We used random-effects meta-regression to test the moderating effects of various moderators on the different relationships of interest. This approach is employed for relationships with at least 20 effect sizes, similar to the method described by Samaha et al. (2014). Accordingly, we could not test the moderating effects for enjoyment, task relevance, habit, result demonstrability, and image since only 8–17 effect sizes were available. The reliability-adjusted correlations were regressed on several moderator variables. While some moderators were dummy coded by this study’s two coders, other moderators were taken from secondary data sources. The dummy-coded variables include health system user (1=staff, 0=patient), voluntariness of IS usage (1=voluntary, 0=involuntary), prior IS experience (1=experience, 0=no experience), study context (1=hospital, 0=non-hospital), remote medicine (1=remote, 0=non-remote), and wearables (1=wearables, 0=non-wearables). The moderators extracted from external data sources include the quality of the country's healthcare system (NUMBEO, 2017) and the life expectancy of the citizens (OECD, 2015). Similar to Van Vaerenbergh et al. (2014), and as suggested by Hox et al. (2010), we also included four dummy variables to represent each variable that correlated with one of the predictors (e.g., usage intention). A summary of how we coded our moderators is shown in Table 3.

[Table 3 about here]

RESULTS

Results of Effect Size Integration

The descriptive results are displayed in Table 4. The results suggest that prior studies of technology acceptance often examined the determinants of usage intention, performance expectancy, and effort expectancy, but less frequently actual usage behavior and attitude.

[Table 4 about here]

Usage behavior. The results indicate that besides usage intention, several predictors also exerted strong direct effects on usage behavior. Effort expectancy, performance expectancy, facilitating conditions, norms, and task relevance displayed direct effects as suggested by UTAUT. In contrast, attitude, output quality, and self-efficacy are non-significant, suggesting indirect effects as proposed by TAM, while value displayed a negative effect. More studies are needed to examine actual usage behavior, particularly for technology anxiety, enjoyment, habit, image, and result demonstrability, which are key variables in major acceptance models.

Usage intention. Most predictors were directly related to usage intention, with technology anxiety and habit being the only exceptions. The strongest effects were displayed by performance expectancy, facilitating conditions, task relevance, and attitude. However, results from effort expectancy, norms, result demonstrability, and self-efficacy are also important determinants of usage intention. The results indicate that predictors from both theories, TAM and UTAUT contribute to a better understanding of usage intention.

Attitude. Several predictors were related to attitudes, including effort expectancy, facilitating conditions, norms, output quality, performance expectancy, and self-efficacy. No effects were observed for anxiety, habit, and value. Interestingly, more research is needed to assess the influence of enjoyment, image, task relevance, and result demonstrability despite these predictors being key in major acceptance theories.

Performance expectancy. Again, the findings suggest that most predictors were related to the assessment of the technology's performance expectancy. In particular, effort expectancy, facilitating conditions, task relevance, and self-efficacy improved usefulness perceptions. The remaining predictors also displayed strong effects. Only anxiety, habit, and value were non-significant. It is interesting to observe that the predictors such as self-efficacy and facilitating conditions impacted performance expectancy, since TAM proposes these variables to have influences on effort expectancy, and UTAUT does not consider these indirect effects at all.

Effort expectancy. The assessment of necessary effort when using the technology depended on the facilitating conditions, task relevance, result demonstrability, self-efficacy, enjoyment, image, norm perceptions, and output quality. The personality trait, technology anxiety, habit, and value perceptions did not influence effort perceptions. It seems that capabilities and expertise were more relevant for the effort perceptions than general personality traits and value assessments.

Most significant relationships were robust against publication bias, with FSNs exceeding the tolerance levels. The significant χ^2 tests of homogeneity and the width of the credibility intervals suggest the presence of moderators causing the variance in effect sizes. The findings suggest that various predictors impact usage behavior and usage intention directly, although TAM proposes indirect effects. At the same time, other predictors were found to influence the mediating effects of effort expectancy, performance expectancy, and attitude, although UTAUT proposes a direct effect on outcomes. Thus, we deemed the test of mediating effect with SEM analysis to be necessary.

Results of Structural Equation Model

We used the correlation matrix in Table 5 to calculate the structural equation models and tested three models against each other, including a direct effects model (model 1; Figure 3), an indirect effects model (model 2), and a combined model (model 3). The combined model only included relationships beyond those discussed in models 1 and 2, which were significant. As Morgan and Hunt (1994) proposed, the models were compared based on the number of significant effects. As displayed in Table 6, we found that models 1 and 3 explained more variance in usage intention and usage behavior than model 2. Also, we observed numerous significant direct effects in models 1 and 3 on usage intention and usage behavior. However, models 2 and 3 indicated that various predictors influence the mediators' performance, effort expectancy, and attitudes. Thus, model 3 outperformed the other two models and will be discussed next.

[Figure 3 and Tables 5–6 about here]

Direct effects. Unified theory proposes that facilitating conditions and usage intentions are related to usage behavior. Both predictors displayed a strong effect in model 3. Contrary to UTAUT predictions, the findings also suggest that effort expectancy and norms display strong positive effects on usage behavior. Together, these determinants explain 19 percent of variance in the usage behavior construct. Unified theory also proposes direct effects of performance expectancy, effort expectancy, norms, facilitating conditions, and value on behavioral intention. The findings suggest that all of these UTAUT predictors except effort expectancy are positively related to usage intention. In addition, the TAM predictors such as output quality and attitudes exert significant effects, and together these variables explain 44 percent of the variance.

Indirect effects. The TAM proposes strong indirect effects through effort expectancy, performance expectancy, and attitudes. We found that performance expectancy and effort expectancy were both related to attitudes, as suggested by TAM. Furthermore, we found significant effects of output quality, value, facilitating conditions, and norms. In line with TAM, the model suggests that effort expectancy, norms, and output quality are positively related to performance expectancy.

Furthermore, the model suggests that facilitating conditions and self-efficacy are related to effort expectancy, also in line with TAM. Contrary to this theory, the results suggest further crossover effects of these variables. Both facilitating conditions and self-efficacy were also found to impact performance expectancy, and norms were found to impact effort expectancy. Perceived value of the technology, which is discussed exclusively by UTAUT also exerts an effect on performance expectancy. The model explains 44 percent of performance expectancy variance and 38 percent of effort expectancy.

Finally, we calculated various predictors' direct, indirect, and total effects (Table 7). As can be seen, the relative importance of the mediators calculated also suggests strong mediating effects. Thus, future studies on the acceptance of healthcare technologies should consider these mediating mechanisms.

Results of Moderator Analysis

The results from the moderator analysis are shown in Table 8.

[Table 8 around here]

Technology. The results of moderator analysis suggest that the effects of several acceptance drivers are context dependent. The results suggest few differences for remote versus non-remote technologies and wearables and other technologies. We observed more differences for other moderators. However, the geographical distance associated with remote services influences the acceptance of these technologies. In the case of HIT with remote technology such as telemedicine, the effort to use displayed a weaker effect, which is slightly surprising. One plausible explanation is that remote technologies have the advantage that the user can step back and rely on the support of experts wherever they are located. Thus, they feel that remote services require less effort on their part and are perceived as easy to use (H1b).

Furthermore, we found that facilitating conditions were less important predictors for wearables although we did not predict this effect (H2). These devices are designed to be user-friendly and straightforward and require little training, making the two predictors lose importance. The remaining hypotheses were found not to be significant for technology context moderators. As such, we can conclude from this finding that, in general, different types of HIT, whether they are telemedicine or wearable devices, do not have significant differences with regard to adoption decisions.

User characteristics. Although both acceptance theories, UTAUT and TAM, propose moderating effects of variables such as user age, the voluntariness of usage, and prior experience, the present study found the most moderating effects to be present for staff versus patients. This finding is important, as often HIT can only be successful if both patients and medical teams adopt them. Consider a technology such as EHR. Although hospitals may adopt EHR, users may be resistant to use it due to privacy concerns (Angst and Agarwal, 2009). In our study, we found that there were differences in HIT acceptance predictors between staff and patients. Specifically, many predictors were less relevant for staff compared with patients, including technology anxiety (H3d), effort expectancy (H3b), facilitating conditions (H3f), norms (H3e), output quality, self-efficacy (H3g), and value perceptions (H3c). This is consistent with previous UTAUT studies that have differentiated technology acceptance behaviors between employees and consumers. Prior UTAUT studies have found that most of the predictors for adoption decisions are more relevant for consumers than for employees. In the context of our research, employees are staff, while consumers are more related to patients. One explanation for our findings could be that medical professionals are trained to use some of the HIT in their work environment and, in some cases, it is also mandatory for them to use HIT. When compared with patients who are less trained to use HIT, these predictors play a lesser role in influencing their acceptance decisions.

Regarding user age, we found facilitating conditions to lose relevance with increasing age (H4a), whereas technology value perceptions gained relevance. This is quite interesting as we would expect that older users would need more facilitating conditions’ support. Nevertheless, older users could also be more experienced in using the technology and, therefore, over time facilitating conditions play a lesser role.

Also, the voluntariness of usage exerts some moderating effects. Technology anxiety, effort expectancy (H5a), facilitating conditions, norms, and self-efficacy (H5b) were more important in voluntary compared with involuntary use contexts. With regard to HIT, previous studies, such as those by Venkatesh et al. (2011), found that the voluntariness of usage has little moderating effect on UTAUT predictors, except on social influence. As they argued, medical professionals such as doctors are given more autonomy in their work and are considered the final decision-maker concerning patient care (Jensen and Aanestad, 2007). Therefore, it is unlikely that an organizational mandate will impact doctors’ decisions to use HIT, which, in the context of their study, was the decision to use EHR. Our study has shown that voluntariness of using HIT has significant moderating effects on many UTAUT predictors, which contradicts existing literature.

Prior experience displayed hardly any moderating influence. We only found effort expectancy (H6f) and output quality (H6b) to gain importance with increasing prior experience. Although most of the hypotheses were rejected for prior experience, our result is consistent with that of Venkatesh et al. (2011), which stated that as an individual gains in experience, the problems they faced with using IT in the early stages, as well as the need for others’ views, will dissipate. Nevertheless, it is interesting to note that general effort expectancy and output quality gain importance with increasing prior experience. It could be that many HIT are quite new to the users and, hence, there is a need to make an effort to learn the new system and ensure that it has good quality output. Most technology adoption studies also focused on initial adoption decisions, such as behavioral intention. Thus, despite having prior computing experience, users may still need time to learn the new HIT in the early stages.

Location. The study provides evidence for the importance of the study location. Our results show that the predictors of HIT acceptance differ in hospital versus non-hospital settings. In hospital settings, effort expectancy, norms, and value perceptions gain importance compared with non-hospital settings. One possibility could be that HIT includes technologies such as EMR and telemedicine in hospitals, where medical professionals such as doctors or nurses would need to learn and apply them in their job. Therefore, it takes effort for them to learn the technology. As for the role of norm, an existing study by Sykes et al. (2011) found that physicians who were better connected to other physicians for advice on their work used HIT (i.e., EMR) less than those who were less connected. Thus, our result slightly contradicts similar and existing studies. In general, however, as none of the effects have been predicted in H7, the hospital context differs from non-hospital settings requiring scholars to differentiate between these contexts.

Healthcare systems. The study suggests some differences for various healthcare systems. The findings indicate that in countries with well-developed healthcare systems and professional healthcare, facilitating conditions is a weaker predictor (HS quality), while self-efficacy gains importance (HS quality, H8a). Also, technology anxiety loses relevance in countries with higher life expectancy (H8c), as well as self-efficacy (H8a). It seems that life expectancy and healthcare systems' quality measure different facets of a country's healthcare system. Specifically, for countries with better healthcare systems, users tend to be less worried about using HIT, and it is not used by only those with high self-efficacy, suggesting that users more commonly use HIT.

GENERAL DISCUSSION

The healthcare systems in many countries face the challenge of ensuring high-quality healthcare services while being effective and efficient at the same time (Chong et al., 2015). HIT can improve healthcare provision if patients and healthcare workers are willing to use the various technologies available to them. The present study, therefore, reviewed empirical research on the user acceptance of healthcare technologies. Specifically, the study intended to contribute to the HIT literature by (1) synthesizing empirical findings on acceptance factors and compiling them in a comprehensive acceptance model, (2) testing the mediating mechanisms of health technology acceptance, and (3) examining contextual differences across different healthcare technologies, users, and locations. Our study used data from 214 independent samples reported in 193 articles and 83,619 technology users from 33 different countries worldwide.

Theoretical Contributions

First, studies examining the acceptance of healthcare technologies usually examine the factors discussed in two key acceptance theories, the TAM and the UTAUT. Our study has tested 14 constructs discussed in these theories and examined their joint impact on HIT usage intention and usage behavior. Specifically, we examined anxiety, image, task relevance, output quality, result demonstrability, and self-efficacy as suggested by TAM. Also, we tested habits and values as suggested by the UTAUT. We considered enjoyment, facilitating conditions, and social norms as proposed by both theories.

Furthermore, we considered effort expectancy, performance expectancy, and attitudes as mediators. We also tested three competing models to determine the best model for predicting the behavioral intention and use of HIT. The results of the analyses suggest that scholars should combine predictors from various theories. In our study, we found strong effects from predictors being exclusively discussed in TAM and UTAUT and predictors being part of both theories. At the same time, some predictors in these theories seem to be less relevant for healthcare technologies (e.g., anxiety, habit). A significant contribution for the research is to consider promising HIT predictors derived from this meta-analysis. Predictors such as output quality, attitude, and self-efficacy, which are not regularly examined in UTAUT/TAM HIT studies, were found to be important HIT antecedents of adoption, and they should be further included in future UTAUT/TAM HIT adoption studies, given their relative importance based on the meta-analysis results.

Second, the model results suggest strong mediating effects of effort expectancy of the technology, performance expectancy, and attitude of users. While TAM suggests these constructs to be full mediators between predictors and technology acceptance, UTAUT proposes that all predictors directly affect usage intention and behavior. The present study clarified that the three constructs represent partial mediators for many predictors. Thus, studies either testing only the direct effects of predictors or only the indirect effects are likely to draw incorrect conclusions about the importance of various acceptance factors. The meta-analysis suggests strong indirect effects for social norms, self-efficacy, and output quality.

Interestingly, the model results also indicate that various predictors impact both effort expectancy and performance expectancy. While TAM suggests that predictors exclusively affect just one of both mediators, our study found strong crossover effects. For example, facilitating conditions help users better understand technology use and make it easier for them, as proposed by TAM. Nevertheless, we also found that training helps users understand the benefits of healthcare technologies. Also, social norms, which are mainly related to performance expectancy perceptions, were found to impact effort expectancy. Thus, the social reference groups seem to shape our beliefs about whether technology is easy to use. These and other crossover effects should be considered in future research. In part, this also addressed some of the criticisms that technology adoption studies have faced (Benbasat and Barki, 2007), where theories such as TAM have continued to be adapted and applied by various scholars despite the lack of advancement in extending our current understanding of factors predicting technology acceptance. However, examining effort expectancy, performance expectancy, and attitude as mediators offers insights into the potential antecedents that influence these factors. Such improved understanding of the antecedents of effort expectancy and performance expectancy in the context of HIT acceptance would allow healthcare organizations to design interventions that would increase user adoption of new HIT. We have also made important contributions to the growing body of technology acceptance literature by showing that a better understanding of attitude as a mediator can enhance the model's predictability about users' acceptance of HIT.

Third, our study contributes to a better understanding of the contextual differences of the technology acceptance factors. Understanding the role of contextual factors is important in IS research (Hong et al., 2014). Guided by Johns (2006) and Weber's (2012) dimensions of context in technology adoption, our meta-analytic data set allowed us to examine the moderators that are more difficult to assess in single studies, such as comparing different health technologies and location differences. Our study assessed several moderators discussed in general acceptance theories such as employee–private user differences, user age, user experience, and voluntariness of usage. These moderators were assessed for healthcare technologies to clarify whether user differences exist for these technologies. Our results suggest that most differences exist when comparing staff with patients as users. For example, the importance of many predictors is stronger for patients than for staff. Existing studies employing UTAUT have found that the technology acceptance behaviors differ between employees and consumers. It was found that UTAUT predictors, in general, are more relevant for users who are consumers rather than employees. This is supported by our study, as employees are staff while consumers are non-staff (i.e., patients). We attribute this finding to the fact that medical professionals are better at using HIT in their work environment. In some cases, it is also mandatory for them to do so. Therefore, these predictors play a lesser role in influencing the acceptance decisions of medical professionals compared with those of patients. We also observed some differences in voluntariness of usage but nearly no differences for users of different age groups and experiences. Many acceptance predictors related to the user have the same effect as across the latter user groups.

Furthermore, we examined whether differences exist for the most recent technologies discussed in the healthcare literature. Using Meuter's (2000) classification of technology types as a guide, we tested whether acceptance differences exist for remote services and wearables. Our study suggests that hardly any differences exist between wearables and other technologies that the user already employs. The acceptance factors have largely the same effect for wearables as for other technologies. The reason may be that wearables were just incremental improvements of technologies that the user is already used to. Similarly, our study found few differences for remote technologies compared with non-remote technologies. We only observed a difference in the predictor effort expectancy, which has a weaker effect for remote technologies, and facilitating conditions, which have a weaker effect for wearables.

Concerning location differences, our study tested moderators that have received little previous attention. We compared hospital settings with non-hospitals and country differences and their different healthcare systems (e.g., quality of the system, life expectancy, and other variables). The results suggest some differences in technology acceptance in hospital settings. In a hospital setting, effort expectancy, norms, and value perceptions are more relevant to predicting users' behavioral intentions and use of HIT. In a hospital setting, most of the users are likely to be healthcare workers. When being introduced to HIT in such a setting, they are more likely to switch to using the system if it is easy to use, if others are also using it, and if the HIT offer more value than the previous system. This finding is consistent with the findings of previous studies, which examined how healthcare workers are being introduced to new HIT such as EMR, RFID, and other new technologies that replace the manual methods of operating the system (Almajali et al., 2016; Hsieh et al., 2015; Hsiao and Chen, 2016). Therefore, when conducting HIT acceptance research, it is vital to consider whether the research is conducted in a hospital versus a non-hospital environment. New technologies in hospitals should include the three predictors we found to be consistently supported in our meta-analysis. Regarding country differences, there are some differences in the willingness to use HIT among countries with different healthcare quality and life expectancy.

We found that self-efficacy gains importance with increasing healthcare quality, while facilitating conditions lose importance. The UTAUT's original predictor, facilitating conditions, is not an important antecedent of HIT behavioral intention and use in countries with high healthcare quality. Also, users from countries with longer life expectancy tend to have less anxiety when using HIT, while users' self-efficacy loses importance. From a theoretical perspective, our results show that it is vital to extend TAM/UTAUT to consider contextual factors related to users, location, and technology types when examining HIT acceptance.

Based on the above discussions, the results of our meta-analysis, and observations based on many HIT adoption literature studies we have examined in this paper, we have also provided a research agenda for HIT acceptance studies (See Table 9).

[Table 9 about here]

Practical Implications

This meta-analysis has several implications for IS managers in the healthcare industry who intend to improve the effectiveness of healthcare provision by providing services more efficiently with the help of healthcare technologies. First, to benefit from technology advantages, managers have to encourage users to use these technologies. Our study helps IS managers to better understand the problems that users perceive regarding these technologies, allowing them to take some measures and provide support. This is an important contribution because prior research was inconclusive regarding the factors that impact technology acceptance, making it difficult for managers to prioritize different measures. Specifically, our study informs managers how to ensure that HIT is perceived as useful and easy to use, and what influences the users' attitudes toward it.

Second, our study also reminds IS managers to develop acceptance strategies for different users, technologies, and locations. Our study suggests that managers should consider the differences in the user's role (staff versus patients), while differences in age and expertise are the less relevant criteria. Our results indicate that most of the acceptance drivers are of lesser relevance for staff than patients and that various drivers gain importance for voluntary use contexts. Furthermore, managers have to be aware of only a few technological differences. The latest technology such as wearables and remote services differ considerably from the other technologies previously introduced. However, managers should consider the location context in their strategic plans. There were different challenges for hospitals compared with non-hospitals as well as for different healthcare systems. To encourage users in hospitals (i.e., healthcare workers) to use HIT, managers should assure the users that the technology is easy to learn. This is important for many healthcare professionals, such as doctors, who are used to the existing method of working and may consider the use of the new HIT as a distraction from their work (Venkatesh et al., 2011). It is also vital that managers consider appointing a champion for using HIT, who should be someone able to influence others to accept the technology (Howell and Higgis, 1990).

Limitations and Further Research

Meta-analyses are generally retrospective studies that rely on data from previous research. Thus, the present study has several limitations that should be addressed in future studies. First, our meta-analysis could only synthesize acceptance factors that have been previously tested for various healthcare technologies. Existing studies often employed TAM and UTAUT as a framework, while predictors from other theories received little attention. Thus, future studies should continue applying different acceptance theories in the healthcare context. For example, the literature lacks studies testing the role of moods in the acceptance of HIT. It may be that the assessment of technology performance expectancy and effort expectancy depends on the mood currently experienced by the user. Meta-analyses are frequently used to direct future research. More studies examining HIT should consider enjoyment, task relevance, habit, result demonstrability, and image since these predictors are under-researched. Specifically, future studies should test the moderators for these predictors because we could not test all the proposed moderating effects with our given data.

Second, our study is limited with regard to the technologies examined. For example, our data set is based on various technologies such as medical records, hospital bedroom scheduling information, wearables, and remote services. Thus, our findings can be generalized to various technologies. Nonetheless, our study could not include all of the latest technologies (e.g., social care robots) since empirical studies lack these technologies. Also, more complex technologies such as remote brain scanners were not examined in this study and deserve greater attention. Once these studies are available, their findings should also be the subject of meta-analysis.

Third, our study examined the acceptance of HIT in 33 countries, including various countries in North America, Europe, and Asia. Although we have covered many of the world's largest and fastest-growing healthcare markets (e.g., the US and China), we lacked studies from other regions, particularly from South America and Africa. It is particularly important to study healthcare technologies in developing countries in more detail to better use technology to improve the healthcare provision in those markets that need it the most. We know from related research that smartphones are essential in these regions for service usages, such as online payment and online banking, that are otherwise unavailable to users. Similarly, future research is encouraged to explore the role of these technologies in less-developed health systems.

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FIGURE 1: CONCEPTUAL MODEL OF HEALTH INFORMATION TECHNOLOGY ACCEPTANCE

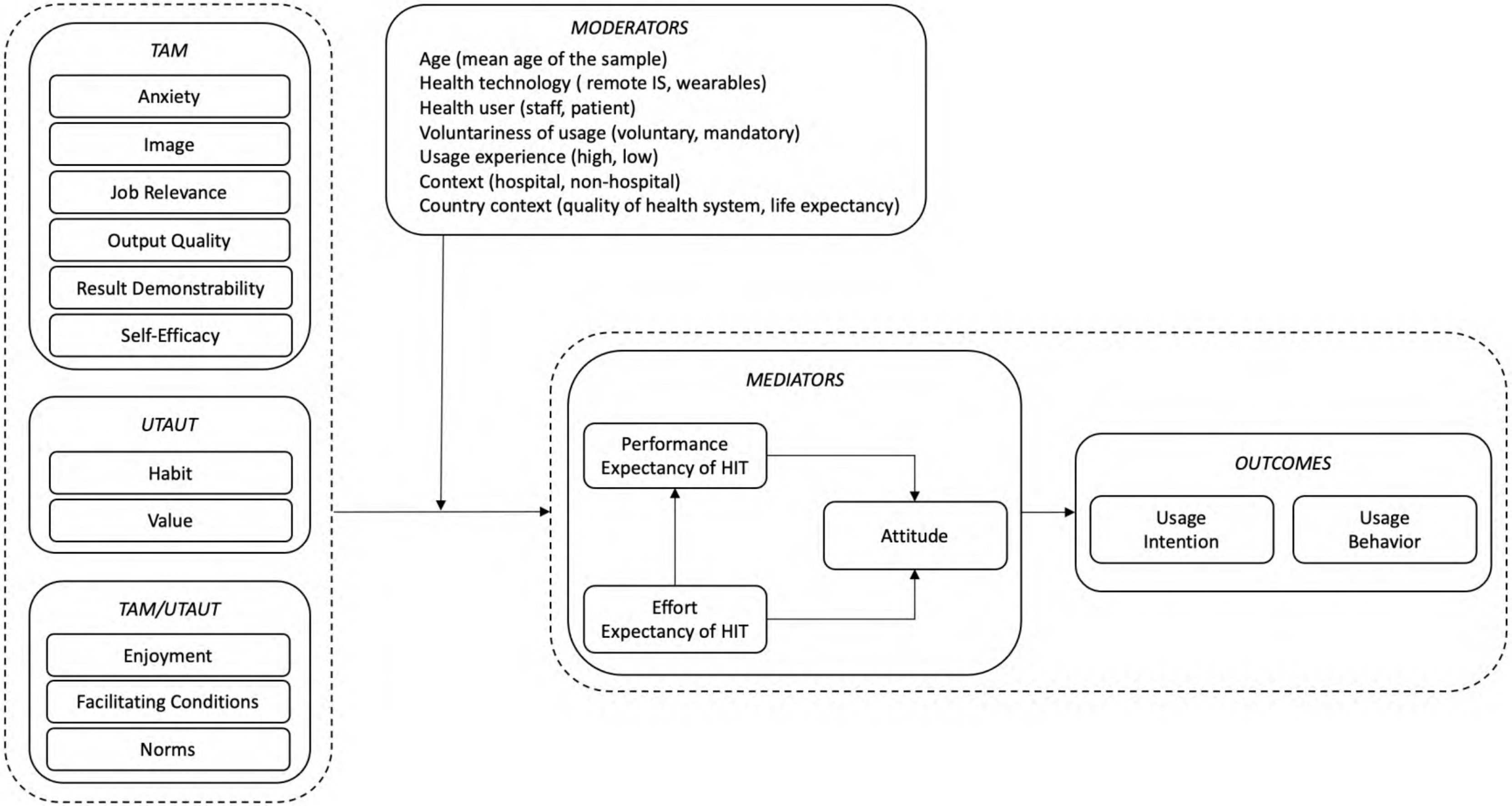

FIGURE 2: STUDY SEARCH AND SELECTION PROCEDURES

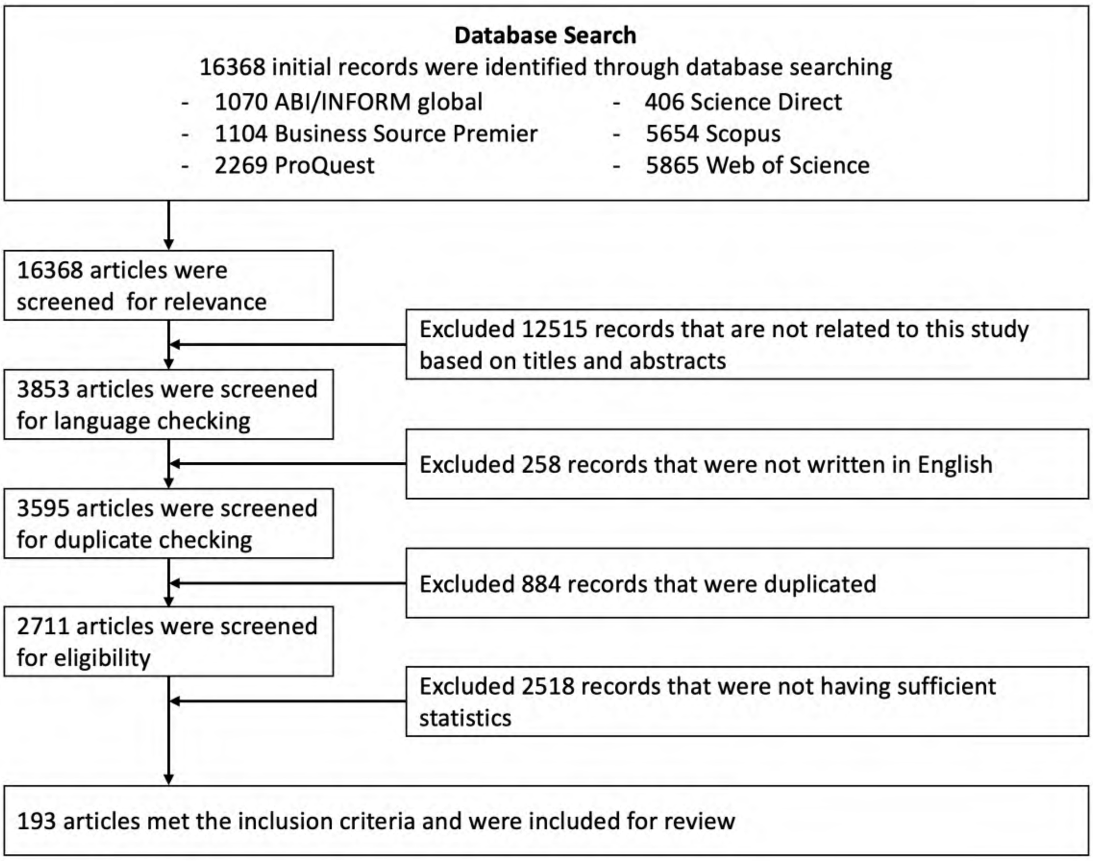

FIGURE 3: MODEL COMPARISON

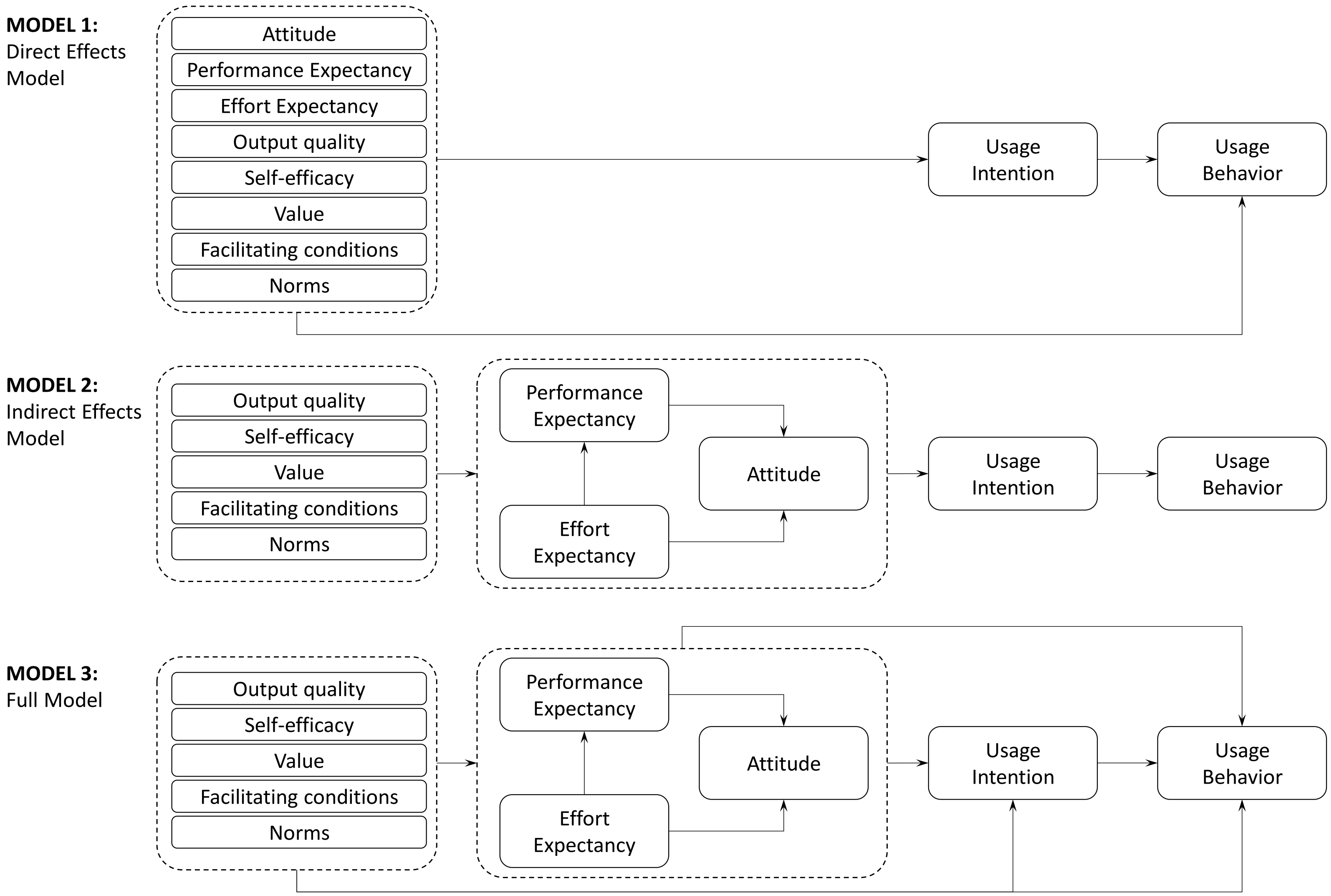

TABLE 1: EXISTING META-ANALYSIS STUDIES ON HIT COMPARED WITH THIS PAPER

	Tao et al. (2020)	**Chauhan and Jaiswal (2017)**	**Our study**
Sample size	• 67	• 111	• 193
Theories used	• TAM/ UTAUT	• TAM	• TAM/UTAUT
Competing models	• None	• None	• Yes
Contextual moderators	• Asian vs Western • General consumers vs patients • mHealth vs non mHealth	• None	• Remote vs. non-remote technologies • Wearable vs. non-wearable technologies • Voluntariness use of technologies versus mandatory • Age and experience of the users • Patients vs healthcare professionals • Hospitals vs non-hospital • Country's healthcare status and life expectancy
SEM	• No • Authors recommended that this method should be applied in future studies.	• No	• Yes
Meta-analysis Method	• Assessments of each predictor's effect size in isolation.	• Assessments of each predictor's effect size in isolation.	• Examined the relative importance of predictors in the structural equation model. • Importance of moderators, tested while controlling for the impact of other contextual factors.

TABLE 2: DEFINITION OF CONSTRUCTS USED IN THE META-ANALYSIS

Construct	Definition	Alias(es)
Anxiety	The degree of an individual's apprehension, or even fear, when she/he is faced with the possibility of using computers (Venkatesh, 2000).	Technology anxiety, computer anxiety, fear
Attitude	An individual's positive or negative feelings (evaluative affect) about performing the targeted behavior (Venkatesh et al. 2003)	—
Effort expectancy	The degree of ease associated with using the technology (Venkatesh et al., 2003).	Ease of use
Enjoyment	The fun or pleasure derived from using a technology (Venkatesh et al., 2012b).	Hedonic benefits, hedonic value
Facilitating conditions	A user's perceptions of the resources and support available to perform a behavior (Venkatesh et al., 2003).	—
Habit	The extent to which people tend to perform behavior automatically because of learning (Venkatesh et al., 2012b).	—
Image	The degree to which an individual perceives that use of an innovation will enhance his or her status in his or her social system (Moore and Benbasat, 1991).	Reputation
Task relevance	The degree to which an individual believes that the target system is applicable to his or her task/job (Venkatesh and Davis, 2000).	Task relevance, task technology fit, task significance
Output quality	The degree to which an individual believes that the system performs his or her job tasks well (Venkatesh and Davis, 2000).	—
Performance expectancy	The degree to which technology will provide benefits to users when performing certain activities (Venkatesh et al., 2003).	Usefulness, relative advantage
Result demonstrability	The degree to which the results of using an innovation are perceived to be tangible (Moore and Benbasat, 1991).	—
Self-efficacy	The degree to which an individual believes that he or she has the ability to perform a specific task/job using the system (Venkatesh 2000).	Computer self-efficacy, Internet self-efficacy
Social norms	The degree to which the user perceives that important others believe he or she should use the technology (Venkatesh et al. 2003).	Peer expectations, expected social conformity, norms
Usage behavior	Actual system use in the context of technology acceptance (Davis et al., 1989).	Actual usage, adoption, continuance usage
Usage intention	The strength of one's intention to perform a specified behavior (Ajzen and Fishbein, 1975).	Continuance intention, usage intention
Value	The individual's cognitive tradeoff between the perceived benefits of the applications and the monetary cost of using them (Dodds et al., 1991).	—

TABLE 3: OPERATIONALIZATION OF MODERATORS

#	Variable	Operationalization
1.	Age	Mean age of the sample
2.	Remote medicine	Dummy-coded whether the sample examines remote IS (1) or non-remote (0).
3.	Wearable	Dummy-coded whether the sample examines wearables (1) or non-wearables (0).
4.	Health system user	Dummy-coded whether the sample examines staff (1) or patient (0).
5.	Voluntariness of usage	Dummy-coded whether the sample adopted the technology on a voluntary (1) or mandatory (0) basis.
6.	Usage experience	Dummy-coded whether the sample user has high experience (1) or low experience (0).
7.	Context	Dummy-coded whether the sample is conducted in the context of a hospital (1) or non-hospital (0) setting.
8.	Quality of health system	NUMBEO (2017)[4] country scores for health Care Index, ranging from low (0) to high (100) quality of life.
9.	Life expectancy	OECD (2015)[5] country scores for healthy life expectancy, ranging from low (0) to (100) high expectancy.

[4] NUMBEO (2017). https://www.numbeo.com/health-care/rankings_by_country.jsp (accessed 25 October 2017).
[5] OECD (2015). Health Status: Life expectancy. https://stats.oecd.org/index.aspx?DataSetCode=HEALTH_STAT (accessed 25 October 2017).

TABLE 4: DESCRIPTIVE RESULTS

Theory	Predictor	Outcome	k	N	r	rw	rwc	SD	CI $_{low}$	CI $_{high}$	CR $_{low}$	CR $_{high}$	Q	p	FSN
TAM	Anxiety	Usage behavior	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Attitude	Usage behavior	3	707	.38	.28	.35	.33	-.03	.72	-.07	.76	58	.00	-
TAM/UTAUT	Behavioral intention	Usage behavior	6	2148	.36	.25	.27	.17	.12	.41	.05	.49	59	.00	300
TAM/UTAUT	Effort expectancy	Usage behavior	12	7054	.36	.26	.30	.16	.20	.39	.09	.50	144	.00	1764
TAM/UTAUT	Enjoyment	Usage behavior	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM/UTAUT	Facilitating conditions	Usage behavior	6	3525	.31	.23	.27	.11	.17	.36	.13	.41	38	.00	398
UTAUT	Habit	Usage behavior	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Image	Usage behavior	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Task relevance	Usage behavior	1	173	.73	.73	.85	-	-	-	-	-	-	-	-
TAM/UTAUT	Norms	Usage behavior	5	3170	.27	.12	.14	.12	.03	.26	-.01	.30	41	.00	129
TAM	Output quality	Usage behavior	2	1248	.43	.14	.16	.25	-.20	.51	-.17	.48	61	.00	-
TAM/UTAUT	Performance expectancy	Usage behavior	12	7122	.41	.37	.42	.23	.29	.56	.12	.72	311	.00	2915
TAM	Result demonstrability	Usage behavior	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Self-efficacy	Usage behavior	2	458	.01	-.07	-.08	.14	-.30	.14	-.26	.10	8	.00	-
UTAUT	Value	Usage behavior	1	1120	-.15	-.15	-.17	-	-	-	-	-	-	-	-
TAM	Anxiety	Behavioral intention	13	3347	-.15	-.17	-.19	.43	-.42	.05	-.74	.37	504	.00	-
TAM	Attitude	Behavioral intention	30	12131	.51	.51	.59	.29	.48	.69	.21	.96	785	.00	30622
TAM/UTAUT	Effort expectancy	Behavioral intention	70	22126	.44	.43	.48	.30	.41	.55	.09	.87	1641	.00	89610
TAM/UTAUT	Enjoyment	Behavioral intention	4	1089	.32	.30	.35	.12	.22	.49	.20	.51	15	.00	147
TAM/UTAUT	Facilitating conditions	Behavioral intention	21	7904	.49	.53	.60	.23	.50	.70	.31	.89	330	.00	13358
UTAUT	Habit	Behavioral intention	3	1168	-.03	-.14	-.16	.53	-.76	.44	-.84	.52	270	.00	-
TAM	Image	Behavioral intention	2	306	.25	.28	.30	.00	.19	.40	.30	.30	1	.22	13
TAM	Task relevance	Behavioral intention	1	84	.70	.70	.73	-	-	-	-	-	-	-	-
TAM/UTAUT	Norms	Behavioral intention	55	18169	.39	.37	.42	.29	.34	.50	.04	.79	1237	.00	44240
TAM	Output quality	Behavioral intention	5	2718	.29	.23	.28	.24	.06	.49	-.03	.58	113	.00	281
TAM/UTAUT	Performance expectancy	Behavioral intention	84	28782	.55	.54	.61	.29	.55	.67	.24	.98	1918	.00	218730
TAM	Result demonstrability	Behavioral intention	3	463	.44	.43	.48	.00	.44	.52	.48	.48	0	.81	92
TAM	Self-efficacy	Behavioral intention	18	5112	.34	.39	.45	.22	.34	.56	.17	.74	206	.00	4194
UTAUT	Value	Behavioral intention	7	1742	.15	.15	.17	.17	.03	.30	-.05	.38	46	.00	98
TAM	Anxiety	Attitude	6	2187	-.15	-.13	-.15	.27	-.37	.07	-.49	.20	126	.00	-
TAM/UTAUT	Effort expectancy	Attitude	25	8429	.52	.59	.67	.38	.52	.82	.18	1.16	930	.00	21832
TAM/UTAUT	Enjoyment	Attitude	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM/UTAUT	Facilitating conditions	Attitude	10	3745	.46	.53	.61	.22	.47	.75	.32	.89	142	.00	3059
UTAUT	Habit	Attitude	2	487	.24	.29	.33	.36	-.18	.83	-.13	.79	49	.00	23

Theory	Predictor	Outcome	k	N	r	rw	rwc	SD	CI $_{low}$	CI $_{high}$	CR $_{low}$	CR $_{high}$	Q	p	FSN
TAM	Image	Attitude	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Task relevance	Attitude	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM/UTAUT	Norms	Attitude	18	6165	.43	.46	.53	.22	.43	.64	.25	.82	234	.00	7263
TAM	Output quality	Attitude	1	122	.38	.38	.41	-	-	-	-	-	-	-	-
TAM/UTAUT	Performance expectancy	Attitude	28	12660	.66	.65	.75	.31	.63	.86	.35	1.14	911	.00	48489
TAM	Result demonstrability	Attitude	-	-	-	-	-	-	-	-	-	-	-	-	-
TAM	Self-efficacy	Attitude	8	3489	.50	.55	.63	.17	.51	.75	.42	.84	77	.00	2538
UTAUT	Value	Attitude	4	755	.20	.27	.31	.48	-.17	.78	-.31	.92	133	.00	-
TAM	Anxiety	Performance expectancy	11	3778	-.17	-.14	-.17	.42	-.42	.09	-.70	.37	521	.00	-
TAM/UTAUT	Effort expectancy	Performance expectancy	81	28507	.55	.53	.60	.31	.53	.67	.20	1.00	2180	.00	200210
TAM/UTAUT	Enjoyment	Performance expectancy	5	1352	.39	.32	.38	.41	.02	.74	-.14	.90	167	.00	288
TAM/UTAUT	Facilitating conditions	Performance expectancy	28	11961	.42	.41	.47	.23	.38	.56	.17	.77	511	.00	16955
UTAUT	Habit	Performance expectancy	2	998	.05	-.09	-.12	.39	-.66	.42	-.61	.38	119	.00	-
TAM	Image	Performance expectancy	4	1037	.35	.39	.44	.11	.31	.56	.29	.58	14	.00	177
TAM	Task relevance	Performance expectancy	4	442	.51	.53	.59	.27	.32	.87	.25	.94	28	.00	167
TAM/UTAUT	Norms	Performance expectancy	52	18487	.40	.38	.44	.26	.36	.51	.10	.77	1010	.00	45029
TAM	Output quality	Performance expectancy	4	1915	.44	.31	.36	.32	.04	.68	-.05	.78	153	.00	335
TAM	Result demonstrability	Performance expectancy	8	3377	.39	.36	.42	.16	.30	.53	.21	.63	74	.00	1198
TAM	Self-efficacy	Performance expectancy	19	5832	.38	.44	.51	.25	.39	.62	.18	.83	298	.00	5978
UTAUT	Value	Performance expectancy	6	2496	.11	.12	.14	.18	-.01	.29	-.09	.37	68	.00	-
TAM	Anxiety	Effort expectancy	9	4228	-.10	-.19	-.23	.46	-.53	.08	-.81	.36	667	.00	-
TAM/UTAUT	Enjoyment	Effort expectancy	5	1352	.34	.28	.33	.19	.15	.51	.09	.57	41	.00	218
TAM/UTAUT	Facilitating conditions	Effort expectancy	29	12136	.49	.48	.54	.27	.44	.64	.20	.89	691	.00	23631
UTAUT	Habit	Effort expectancy	2	998	-.07	-.10	-.11	.06	-.22	.00	-.19	-.03	5	.02	-
TAM	Image	Effort expectancy	2	306	.20	.17	.19	.00	.11	.26	.19	.19	1	.38	5
TAM	Task relevance	Effort expectancy	2	257	.50	.52	.57	.00	.48	.66	.57	.57	1	.35	46
TAM/UTAUT	Norms	Effort expectancy	45	15397	.33	.36	.42	.25	.35	.49	.11	.74	729	.00	25563
TAM	Output quality	Effort expectancy	8	4166	.29	.19	.23	.17	.10	.35	.00	.45	100	.00	571
TAM	Result demonstrability	Effort expectancy	6	2605	.76	.96	1.11	.26	.91	1.32	.78	1.44	128	.00	3584
TAM	Self-efficacy	Effort expectancy	20	7206	.40	.40	.47	.22	.37	.56	.19	.74	266	.00	7272
UTAUT	Value	Effort expectancy	5	2328	.05	.08	.09	.17	-.06	.25	-.13	.32	59	.00	-

k=number of effect sizes; N=cumulative sample size; r=average correlation; rw = sample-size-weighted correlation; rwc = sample-size-weighted reliability-corrected correlation; CI=confidence interval; CR=credibility interval; Q=Q-test of homogeneity; FSN=Fail-safe N.

TABLE 5: CORRELATION MATRIX

Construct	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
1. Attitude	1.00									
2. Behavioral intention	.54	1.00								
3. Effort expectancy	.59	.43	1.00							
4. Facilitating conditions	.63	.51	.53	1.00						
5. Norms	.52	.43	.47	.50	1.00					
6. Output quality	.38	.24	.19	.19	.36	1.00				
7. Performance expectancy	.68	.58	.56	.50	.48	.32	1.00			
8. Self-efficacy	.58	.41	.53	.55	.53	.40	.48	1.00		
9. Usage behavior	.24	.31	.35	.33	.36	.13	.29	.07	1.00	
10. Value	.25	.31	.13	.21	.14	-.09	.21	.05	.09	1.00

Notes. The harmonic mean is 2,132.

TABLE 6: RESULTS OF MODEL COMPARISON

Predictor	Outcome	Model 1: Direct effects			Model 2: Indirect effects			Model 3: Full model		
		B	t	R^2	B	t	R^2	B	t	R^2
Usage intention	Usage behavior	.11*	4.71	19%	.31*	15.06	10%	.11*	4.71	19%
Effort expectancy	Usage behavior	.17*	6.80		–			.17*	6.80	
Facilitating conditions	Usage behavior	.09*	3.57		–			.09*	3.57	
Norms	Usage behavior	.19*	7.92		–			.19*	7.92	
Attitude	Usage intention	.07*	2.67	44%	.54*	29.64	29%	.07*	2.67	44%
Performance exp.	Usage intention	.32*	13.82		–			.32*	13.82	
Output quality	Usage intention	.05*	2.81		–			.05*	2.81	
Value	Usage intention	.17*	9.97		–			.17*	9.97	
Facilitating conditions	Usage intention	.20*	9.07		–			.20*	9.06	
Norms	Usage intention	.08*	3.87		–			.08*	3.88	
Performance exp.	Attitude	–			.51*	28.28		.33*	18.97	
Effort expectancy	Attitude	–			.31*	16.91	53%	.18*	10.43	63%
Output quality	Attitude	–			–			.18*	11.97	
Value	Attitude	–			–			.11*	7.62	
Facilitating conditions	Attitude	–			–			.29*	16.86	
Norms	Attitude	–			–			.06*	3.34	
Effort expectancy	Performance exp.	–			.32*	15.70	44%	.32*	15.70	44%
Output quality	Performance exp.	–			.16*	8.80		.16*	8.80	
Self-efficacy	Performance exp.	–			.08*	3.58		.08*	3.58	
Value	Performance exp.	–			.13*	7.50		.13*	7.50	
Facilitating conditions	Performance exp.	–			.16*	7.57		.16*	7.57	
Norms	Performance exp.	–			.13*	6.14		.13*	6.14	
Self-efficacy	Effort expectancy	–			.28*	12.70		.28*	12.70	
Facilitating conditions	Effort expectancy	–			.29*	13.53	38%	.29*	13.53	38%
Norms	Effort expectancy	–			.18*	8.55		.18*	8.55	

* p < .05 level. The models display only significant relationships.

TABLE 7: DIRECT, INDIRECT, AND TOTAL EFFECTS

	Usage behavior				Usage intention				Attitude				Performance expect.				Effort expectancy			
Determinant	**D**	**I**	**T**	**Rel.**	**D**	**I**	**T**	**Rel.**	**D**	**I**	**T**	**Rel.**	**D**	**I**	**T**	**Rel.**	**D**	**I**	**T**	**Rel.**
Behavioral intention	.11	–	.11																	
Attitude	–	.01	.01	100%	.07	–	.07													
Performance exp.	–	.04	.04	100%	.32	.02	.35	7%	.33	–	.33									
Effort expectancy	.17	.02	.18	9%	.03	.13	.16	80%	.18	.11	.29	37%	.32	–	.32					
Output quality	–	.01	.01	100%	.05	.07	.12	57%	.18	.05	.23	23%	.16	–	.16	0%	–	–	–	–
Self-efficacy	–	.05	.05	100%	–	.07	.07	100%	–	.11	.11	100%	.08	.09	.17	53%	.28	–	.28	0%
Value	–	.03	.03	100%	.17	.05	.22	23%	.11	.04	.15	29%	.13	–	.13	0%	–	–	–	–
Facilitating conditions	.09	.08	.18	48%	.20	.12	.32	38%	.29	.14	.42	32%	.16	.09	.26	36%	.29	–	.29	0%
Norms	.19	.05	.24	20%	.08	.08	.16	49%	.06	.09	.15	63%	.13	.06	.19	31%	.18	–	.18	0%

D = direct effect; I = indirect effect; T = total effect; Rel. = relative importance of indirect effect to total effect.

TABLE 8: RESULTS OF MODERATOR ANALYSIS

Predictor	k	Remote IS (other)	Wearable (others)	Staff (patient)	Age	Voluntar. (invol.)	Exp. (no exper.)	Hospital (others)	HS quality	Life exp.	UB	UI	PE	EE
Anxiety	68	.11	.03	-.27*	.19	.31*	.16	.28	.02	-.27*	.00	-.05	-.05	.03
Effort expectancy	314	-.14*	.08	-.15*	.04	.15*	.15*	.15*	.00	-.03	-.13*	-.13	.07	–
Facilitating conditions	234	-.02	-.16*	-.26*	-.16*	.20*	.08	-.07	-.11*	.02	-.23*	-.15	-.13	-.10
Norms	331	-.01	-.09	-.13*	-.07	.11*	-.03	.15*	-.07	-.08	-.03	-.01	.03	-.08
Output quality	20	.30	.32	-.52*	.12	–	.92*	–	-.08	.29	.32*	.03	.09	–
Performance expectancy	171	-.08	.11	-.04	-.02	.04	.07	.02	-.10	.11	-.23*	–	–	–
Result demonstrability	20	–	.09	-.08	-.48	–	-.23	.57	.37	.07	–	-.37*	-.64*	–
Self-efficacy	118	-.18	-.03	-.24*	.08	.22*	.10	.11	.27*	-.30*	-.19*	-.18	-.17	-.21
Value	47	.10	.13	-.61*	.37*	–	.21	.27*	-.20	-.02	-.13	.08	.04	-.14

* p < .05 level. The dashes in the table indicate that moderator information was not available. The coefficients in the table can be interpreted as follows: The positive reliability-corrected correlations of effort expectancy are weaker for remote IS (-.14) and staff (-.15), while they are stronger for voluntary usage contexts (.15), experienced users (.15), and hospitals (.15). Also, the correlations are weaker for effort expectancy-behavior correlations (-.13).

TABLE 9: RESEARCH AGENDA ON HIT ADOPTION STUDIES

Issues	Key Illustrative Recommendations
Examine theoretically meaningful predictors	• Consider the predictors that are beyond UTAUT/TAM studies. • Identify other promising theories, such as activity theory, privacy calculus theory, and status quo bias theory, that have been examined in the HIT context but not sufficiently studied to be included in this meta-analysis study. • Predictors such as output quality, value, and self-efficacy, which are not regularly examined in UTAUT/TAM studies, should be further included in HIT adoption studies, given their relative importance based on the meta-analysis results. • Continue testing the theoretical boundaries of the existing technology acceptance theories in the context of HIT.
Expand the focus on HIT technology adoption	• Examine the effects of individual-level variables (e.g., technology use) on outcomes at a higher level (e.g., hospitals' performances). • Test the interactions between higher-level predictors (e.g., healthcare senior leadership style) and lower-level moderators (doctors/nurses innovativeness). • Theorize more complex interaction effects such as between culture in a country and healthcare quality. • Assess multi-level mediation between user characteristics on HIT use and the impact of technology use on hospital/clinic performance. • Examine more levels of analysis, including individuals, dyads, and teams in the healthcare setting.
Use novel theories and frameworks to extend the range of mediators, moderators, and outcomes of HIT technology use	• Employ context dimensions from previous studies such as Johns (2006) and Weber (2012) to examine moderators related to user class, technology class, and location class to name a few. • Instead of testing the direct effects of predictors as most HIT adoption studies have done, studies should consider examining performance expectancy, effort expectancy, and attitude as potential mediators for HIT adoption. • Employ theories from cultural studies to assess novel moderators (e.g., concept of cross-national differences; Swoboda et al., 2016). • Examine whether the healthcare quality of countries will affect the implementation of HIT at the organizational and individual user level. • Differentiate between assimilation, diffusion, and routinization of technology use, which has been under-studied. • Focus on the outcomes of implementing HIT technology (e.g., patient satisfactions).
Use different research designs	• Employ observational studies and qualitative studies. • Consider studying longitudinal effects in HIT adoption by employing methods such as latent growth modelling. • Investigate the changing difference of HIT predictors, e.g. assess whether theoretical models applied in HIT differ for initial compared with repeated technology use.

Appendix A. Summary of recent HIT-related adoption studies (2015–2020)

Authors	**Theory used**	**Types of IS studied**	**Summary of study**
Abdelhamid, M. (2018)	UTAUT	Health information exchanges	• This study examines a platform that provides sharing of information between healthcare providers and payers in different hospitals and regions. • The paper claims to extend UTAUT, but there is no UTAUT predictor except perceived usefulness (instead of effort expectancy). • Factors such as privacy, trust, and health concerns were proposed and found to be significant. • UTAUT moderators were not proposed in this study.
Agarwal et al. (2017)	Ability-motivation framework/ Self-determination theory	Electronic health record	• Ability-motivation framework and self-determination theory are applied to investigate the adoption of EHR at the level of the physician practice. • Results show that while the ability components exhibit direct effects on adoption, the motivational components and their relationships to adoption are more complex. • While physicians may see value in adopting an EHRS, this intrinsic motivator can be undermined by extrinsic pressures from external sources, e.g. regulatory agencies, pharmaceutical companies and peer practices.
Alaiad and Zhou (2015)	UTAUT	Wireless sensor network – smart home healthcare systems	• This paper examined patients' intention to use wireless sensor network – smart home healthcare systems based on the UTAUT model. • 83 patients participated in this survey study. • The paper did not apply the full UTAUT and only applied performance expectancy, effort expectancy, and social influence. • The model was also extended using cost and life quality expectancy. • The results confirmed the proposed model.

Authors	Theory used	Types of IS studied	Summary of study
Almajali et al. (2016)	TAM	ERP	• The authors of the paper examined the factors that influence the enterprise resources planning (ERP) system implementation success. • TAM's ease of use was used as a predictor to user satisfaction and ERP implementation success. • 175 respondents' survey data were collected and tested using SEM. • The paper also included other determinants of user satisfaction such as training and supportive leadership. • Perceived usefulness, which is part of the TAM model, was omitted from the research.
Basak et al. (2015)	TAM	Personal digital assistant (PDA)	• Behavioral intention to use personal digital assistant (PDA) technology among physicians in Turkey was examined. • An extended TAM was applied. • TAM was extended with subjective norms, personal innovativeness, computer self-efficacy, and perceived enjoyment. • SEM was applied to test the data collected from 339 physicians in Turkey to confirm the model. • No moderators were proposed in the study.
Bautista et al. (2018)	UTAUT	Electronic health records	• This study was conducted in Jordan and collected nurses responses on their continuance intention to electronic health records. • UTAUT was the theoretical foundation of this study and top management support was extended to the model. • Practice environment and nurse specialty were proposed as moderators to UTAUT predictors. • No discussion on the expectation confirmation model. • The paper excluded UTAUT moderators.
Byomire and Maiga (2015)	TAM/UTAUT	Mobile technology	• This research focused on the adoption of mobile phones for maternal healthcare in Uganda. • Maternal healthcare professionals were the respondents for this study.

Authors	Theory used	Types of IS studied	Summary of study
			• The adoption mobile phone in maternal healthcare are influenced by TAM and UTAUT variables such as perceived ease of use, perceived usefulness, facilitating conditions, social influence, perceived value, workflow practices, and behavioral intention to use mobile phones in maternal healthcare. • No mediator or moderator was proposed.
Chang et al. (2015)	TAM	Web-based appointment system	• Chang et al. (2015) examined the factors affecting the user acceptance of WAS by integrating TAM with the constructs of service quality. • User experience, website quality, and service quality were examined as predictors of perceived ease of use and perceived usefulness. • No moderator was proposed in the model.
Cimperman et al. (2016)	TAM/UTAUT	Telehealth	• A model for predicting the factors affecting older users' acceptance of home telehealth services (HTS) was proposed. • Data were collected from 400 participants aged 50 years and above in Slovenia. • The predictors affecting acceptance behavior are performance expectancy, effort expectancy, facilitating conditions, and perceived security. • No moderator was included in the study.
Diño et al. (2015)	UTAUT	Telehealth	• This paper examined the behavioral intention for telehealth use among Filipino elderly based on UTAUT. • Their conceptual model includes performance expectancy, effort expectancy, and social influence. • These factors in turn are moderated by gender. • Facilitating conditions are left out of their study without providing strong discussion. • A sample of 82 users was selected to test their research model.

Authors	Theory used	Types of IS studied	Summary of study
Dhaggara et al. (2020)	TAM	General technology in healthcare	• The study examines Indian users' intention to use technology in healthcare service quality. • TAM was extended by including trust and privacy concern. • The study confirms the model proposed. • The study excluded attitude from TAM and no moderator was proposed in the study.
Francis (2019)	UTAUT2	Patient self-monitoring device	• This study examines healthcare providers' behavioral intentions and use of a self-monitoring device data for the electronic healthcare system. • UTAUT2 was used as the theoretical foundation of the study. • UTAUT predictors were found to have significant relationships with behavioral intention and use of the device. • The moderators of UTAUT2 were excluded from the study.
Gao et al. (2015)	UTAUT2/PMT/Privacy Calculus Theory	Wearable device	• Factors that can predict consumers' intention to adopt wearable technology in healthcare are tested. • An integrated acceptance model was developed based on UTAUT2 and protection motivation theory (PMT), and privacy calculus theory. • Findings indicate that healthcare wearable technology is affected by factors from technology, health, and privacy perspectives. • Users are affected more from hedonic motivation, functional congruence, social influence, perceived privacy risk, and perceived vulnerability, but medical device users pay more attention to perceived expectancy, self-efficacy, effort expectancy, and perceived severity. • The study did not apply the full UTAUT model by omitting some variables (e.g. price value) and the moderators in UTAUT2.
Guo et al. (2015)	TAM/PMT	Mobile health	• This paper tested a technology acceptance model based on the protection motivation theory.

Authors	Theory used	Types of IS studied	Summary of study
			• Results show that threat appraisal and coping appraisal factors influence adoption intention through attitude. • Gender and age have a different moderating effect on threat appraisal and coping appraisal factors
Guo et al. (2016)	Privacy-personalization paradox	Mobile health service	• This research developed an attribute–perception–intention model based on the privacy-personalization paradox factors as predictors of mobile health service adoption. • Trust is proposed as a mediator of privacy concerns and perceived personalization. • Results showed that that perceived personalization and privacy concerns are positively and negatively associated with behavior intention. • Trust mediates the relationships between perceived personalization, privacy concerns, and adoption intention.
Hsiao and Tang (2015)	TAM	Mobile health service	• This study includes variables derived from sociological, technological, and individual attributes. • Data were collected from 338 users to examine predictors such as perceived ubiquity, personal health knowledge, and perceived need for healthcare in their model. • Results confirm the role of perceived ubiquity, personal health knowledge, and perceived need for healthcare in predicting user attitude, which in turn influence adoption intention decision.
Hsieh (2015)	TPB/status quo bias theory	Cloud computing	• An integrated model was proposed to explain healthcare professionals' intention to use the health cloud service as well as their intention to resist it. • The findings revealed that healthcare professionals' resistance to the use of the cloud computing is due to regret avoidance, inertia, perceived value, switching costs, and perceived threat. • Attitude, subjective norm, and perceived behaviour control have a direct positive influence on their intention to use cloud computing.

Authors	Theory used	Types of IS studied	Summary of study
Hsiao and Chen (2016)	TAM/activity theory	Computerized clinical practice guidelines	• TAM and activity theory are employed in this study. • Data were collected from physicians from hospitals that have implemented the system. • Results suggest that users' attitudes toward using computerized clinical practice guidelines is influenced by organizational support, perceived usefulness, and social influence.
Hsieh (2016)	UTAUT/status quo bias theory	Cloud computing	• Extending Hsieh (2015), this study examines cloud services in healthcare, but from the patient's perspective in terms of their intention to use and resist the system. • The findings revealed that patients' resistance to use cloud service is related to sunk costs, inertia, perceived value, transition costs, and uncertainty. • UTAUT factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions are shown to have a positive and direct effect on patients' intention to use the cloud services. • The model, however, neglected the moderators proposed in UTAUT.
Hsieh et al. (2017)	UTAUT/protection motivation theory (PMT)	Personal health record	• The study examined users' intention to adopt the personal health record system in China. • Although UTAUT is proposed, the model is not complete as it does not include facilitating conditions. • Terms applied are from TAM instead of UTAUT (e.g. perceived ease of use instead of effort expectancy). • Factors from PMT were selected although not all variables are from the theory. • Moderators from UTAUT are not examined.

Authors	Theory used	Types of IS studied	Summary of study
Ifinedo (2016)	TAM	Information systems	• This research examines the moderating effects of demographic factors such as educational level and age and individual characteristics such as years of work experience and computer knowledge on nurses' adoption of information systems. • TAM was employed as the base model in this research. • Education and computer knowledge have moderating effects on the influences of perceived ease of use and perceived usefulness on adoption attitude. • However, nurses' years of nursing experience and age have no significant result.
Jeon and Park (2015)	TAM	Healthcare mobile app	• This study examines users' adoption of a mobile healthcare app, i.e. mobile obesity-management app. • The model proposed is based on TAM but has been extended to include compatibility, self-efficacy, and technical support and training. • 94 Android smartphone users used the developed mobile app for two weeks, and then they completed a survey that measured the predictors for their intention to use the app. • The results showed that compatibility, perceived usefulness, and perceived ease of use influence the behavioral intention to use the mobile obesity-management app. • Technical support and training also affect the perceived ease of use. • Self-efficacy's influence on perceived usefulness and perceived ease of use was not supported in this study. • As the study is based on users who have used the app for 2 weeks, theory such as the Expectations Confirmation Model (ECM) could be employed, although this is not mentioned in the paper.
Kalavani et al. (2020)	UTAUT	Evidence-based medical databases	• Users’ general acceptance of evidence-based medical database was examined.

Authors	Theory used	Types of IS studied	Summary of study
			• UTAUT was applied but no moderator was proposed, except the predictors. • The paper showed that all four UTAUT factors have an influence on users’ behavioral intention to use the database. • The study only examined the mean value of the predictors instead of conducting multivariate data analysis such as SEM.
Keikhosrokiani et al. (2016)	UTAUT/TAM/TPB	Mobile healthcare information systems	• This paper examines users' intentions to adopt mobile healthcare information systems based in Malaysia. • In total, 123 users participated in the study, which built its model based on UTAUT, TAM, and TPB. • The factors examined in this study are: self-efficacy, anxiety, effort expectancy, performance expectancy, attitude, and behavioral intention to use. • Despite claiming to build their concept from UTAUT, TAM, and TPB, the limitation of this study is that all three models are not fully adopted, and there is little explanation why are some variables selected or omitted.
Kim et al. (2016)	UTAUT/TAM	Electronic health record	• The paper examined the factors that influence users' intentions to utilize a mobile electronic health records system. • Both online survey as well as log file data were used to measure user actual use. • Data were collected from 449 healthcare professionals in a university hospital for seven months. • Results showed that doctors and nurses used the system’s menus to view the inpatient lists, alerts, and patients' clinical data frequently. • Users' intentions to use the system are influenced by performance expectancy and attitude.
Krishnan et al. (2015)	TRA/TAM/UTAUT	Consumer health informatics	• This study examines the factors influencing consumer intention to adopt Consumer Health Informatics (CHI) application.

Authors	Theory used	Types of IS studied	Summary of study
			• The authors developed their model based on Theory of Reasoned Action, TAM, and UTAUT. • The findings revealed that hedonic motivation, perceived ease of use, and performance expectancy influence the intention to adopt HCI. • Overall, UTAUT is not fully adopted, and TAM and TRA, which are part of UTAUT, are included in the study. • No moderator or mediator was tested in the study.
Lai et al. (2015)	TAM	Mobile registration system	• The modified TAM (MTAM) was applied in this study on the use of mobile clinic registration system in Taiwan. • Perceived ease of use and perceived usefulness of the technology influence users' attitudes toward technology use.
Lee et al. (2020)	UTAUT/information systems quality	E-appointment system	• An integrated UTAUT and information systems quality model was applied to examine patients' continuance intention to use the e-appointment system. • Predictors such as performance expectancy, facilitating conditions, service quality, and information quality were found to have a significant influence on continuance intention. • The paper did not discuss the expectation confirmation model although it is studying in the context of continuance intention. • No moderator was proposed in the study.
Nisha et al. (2016)	UTAUT	m-Health services	• The role of service quality and knowledge as factors influencing future use intentions of m-Health services in Bangladesh were tested. • Using the UTAUT model as the theoretical model, data collected from 1000 respondents were analyzed. • Main findings indicate that certain aspects of service qualities such as reliability, privacy, responsiveness, empathy, and information quality, along with other factors such as facilitating conditions, effort expectancy, performance expectancy, and social influence

Authors	Theory used	Types of IS studied	Summary of study
			play an important role in the overall perceptions of m-Health services. • UTAUT moderators were not proposed and tested.
Song et al. (2015)	TAM	Bar code medication administration technology	• This paper adopts the TAM model to study hospital nurses' behavioral intention to use bar code medication administration technology. • The relationships among patient safety culture, perceived usefulness, perceived ease of use, and behavioral intention to use the technology were examined with data collected from cross-sectional surveys with 163 nurses. • No moderators or mediators were proposed in the model studied.
Van Der Vaart et al. (2016)	UTAUT	Online self-management interventions	• Using UTAUT as the theoretical model, this study investigated the use of and intention to use guided online psychological self-management interventions and the main barriers to the use of such technologies. • An online survey was conducted among mental health counsellors (MHCs) in GP practices and primary care psychologists (PCP) in mental healthcare practices. • Results confirmed the performance expectancy, effort expectancy, and facilitating conditions of the model, which are significant predictors of usage intention. • The paper did not test moderators from UTAUT.
Venugopal et al. (2018)	UTAUT	Electronic health record and telemedicine	• UTAUT predictors were employed to examine clinical staff intention to adopt electronic health records and telemedicine. • All four UTAUT predictors were found to influence behavioral intention. • The study, however, did not replicate UTAUT as moderators were excluded from the study.

Authors	Theory used	Types of IS studied	Summary of study
Yuan et al. (2016)	UTAUT2	Health and fitness apps	• Authors of this study adopted the UTAUT2 model to assess the predictors of users' intention to adopt health and fitness apps. • A survey with 317 college-aged smartphone users in a university in the US revealed that performance expectancy, hedonic motivations, price value, and habit were significant predictors of users' intention of continued usage of health and fitness apps. • Effort expectancy, social influence, and facilitating conditions were not found to predict users' intention of continued usage of those apps. • The paper only examined behavioral intention and neglected use behavior. • Moderators in UTAUT2 were neglected in this study.
Zhou et al. (2019)	UTAUT	Hospital electronic information management systems	• Nurses' intention to use hospital electronic information management systems was examined. • UTAUT was applied to test the model. • UTAUT factors such as performance expectancy and effort expectancy were neglected. • Age, gender, and voluntariness were used as direct predictors of behavioral intention instead of moderators.
Zhou et al. (2019)	TAM	Telehealth	• Predictors of telehealth adoption by the elderly in China were investigated. • The extended TAM model was proposed, which included affordability, comfort, professionalism, safety, information quality, and medical service satisfaction. • Perceived usefulness and attitude were neglected in the model. • No moderator was proposed.

Appendix B. List of papers used in meta-analysis

Abdekhoda, M., Ahmadi, M., Dehnad, A., Hosseini, A.F., 2014. Information technology acceptance in health information management. Methods of Information in Medicine. 53 (1), 14-20.

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