Extending the Unified Theory of Acceptance and Use of Technology (UTAUT) to understand Electronic Healthcare Record implementation: The role of perceived goal attainment, perceived velocity and team learning behaviour

BY

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ABSTRACT

With the strong on-going interest and effort to push investment in the implementation of Electronic healthcare record (EHR), understanding the factors that will drive the use of the system has important scientific and practical significance. However, there is sparse literature on understanding what influence healthcare professionals (i.e. doctors, paraprofessionals and administrative personnel)'s motivation to learn and use EHR. Against this backdrop, the key objective of this thesis is to examine the factors that influence healthcare professionals' behavioural intention to adopt and actual use of electronic healthcare record in Malaysia. The research questions for this thesis are 1) Can Unified Theory of Acceptance and Use of Technology (UTAUT) factors predict healthcare professionals' motivation to learn and the behavioural intention to adopt and accept EHR? 2) Can the extended model of UTAUT that includes goal attainment, perceived velocity and team learning behaviour better predict healthcare professionals' motivation to learn and the behavioural intention to adopt and accept EHR? and 3) Is there a significant relationship between motivation to learn EHR and EHR behavioural intention to adoption and acceptance of EHR among Malaysian healthcare professionals?

The key theoretical underpinning this research is based on UTAUT. UTAUT is extended in this research by integrating theories from goal pursuits (i.e. perceive goal attainment and perceived velocity) and team learning behaviour. Furthermore, the role of motivation to learn EHR in influencing behavioural intention and actual use of EHR was also studied. Working together with a Malaysian medical group that has more than 200 clinics, longitudinal data was

collected from doctors, paraprofessionals and administrators in three waves over 6 months periods during pre-implementation of the EHR (T1), 2-3 months (T2) during implementation, and 4-5 months (T3) after sustained continuous implementation. Overall, 520 surveys were collecting during pre-implementation at T1, 210 during implementation in month 2-3 at T2, and 182 in sustained implementation in month 4-5 at T3. The data were analysed using PLS-SEM.

The results showed that while UTAUT can partially explain healthcare professionals' behavioural intention and actual use of EHR, while the extended model with new variables introduced in this thesis significantly explain the mechanisms leading to EHR adoption. Furthermore, the results show that the adoption factors vary in their relationships with behavioural intention and actual use of EHR at different implementation stages.

This thesis contributes to previous EHR adoption studies as well as UTAUT literature by replicating UTAUT in this research to test if UTAUT's can be replicated in an Asian context, as well as providing an improved UTAUT to study EHR adoption. Besides integrating UTAUT with theories related to goal pursuit, team learning behaviour and motivation to learn information systems, the new model was also tested with longitudinal data, which has an advantage over cross-sectional data, in that it is able to test the model from implementation stage to adoption.

This thesis also informs practice by providing guidelines and strategies to healthcare companies that plan to implement EHR. Contrary to many previous practices employed by organizations, rather than having a one size fits all training programme, companies can highlight on the features (e.g. performance expectancy) or easiness to learn the system (e.g. effort expectancy) to different user groups. Clinics and hospitals that are implementing EHR should note that motivation to learning EHR will lead to better actual use of the system in the early stage of EHR implementation. Therefore healthcare professionals should be provided with the necessary facilities and training to motivate them to learn. Given that team learning behaviour influence users' motivation to adopt EHR, companies can also consider forming small group, need-based trainings so that learning can be fun with strong group dynamics. These groupings can also be based on task or job functions so that users can learn from each other and keep motivation level high.

Lastly, in the early stage of EHR implementation, companies should continue to ensure that employees are motivated to learn how to use EHR and to provide support when needed so that staff are encouraged and motivated to continue using the system.

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CHAPTER 1 INTRODUCTION

1.0 Introduction

The healthcare industry is one of the most important and fastest growing industries in the world (Chong and Chan, 2012). It is estimated that spending on the healthcare industry will reach nearly 20 percent of the United States' Gross Domestic Product (GDP) by 2025 (Chong and Chan, 2012). Global healthcare spending will also see an increase and double to 18.28 trillion dollars by 2040 (Dielman et al., 2016). Although there are many new developments and growth in the healthcare industry, the industry itself is facing enormous challenges to ensure the delivery of high quality, efficient and timely services, while ensuring that the cost is affordable to people (Chong et al., 2015). Over the last few years, researchers have conducted extensive studies on the healthcare industry with the aim of providing guidance on how the healthcare industry can improve its performance while not overly increasing its costs (Dobrzykowski et al., 2014). A common theme of these studies is the call on the healthcare industry to better apply information technologies (IT) to the healthcare sector in order to ensure that their operations are efficient, and that better services are delivered to patients. Electronic health records (EHR), radio frequency identification (RFID), and cloud computing are some healthcare information technologies (HIT) that have been implemented by the healthcare industry to improve the management of their supply chain and operation performance, as well as offering better services to patients such as reduced waiting times, ensuring that there are less errors in record handling, just to name a few of the benefits from using IT (Kohli and Tan, 2016; Chong et al.,

2015). Information systems (IS) and operations management scholars have long stressed the importance of the need to ensure that there is successful acceptance of IT in the healthcare industry in order to achieve cost savings and service improvements (Adomavicius et al. 2013; Autry et al. 2010; Froehle and Roth 2004).

One of the main reasons why HIT has been touted as a vital technology that can help address the challenges faced by the healthcare industry and to improve its values offering is that the potential benefits to be gained from HIT implementation can be carried forward not only to the hospitals, but also to other stakeholders such as patients, suppliers and government (Venkatesh et al., 2011). The term HIT is broadly defined as IT that is applied to the health and health care industry. Some of the common examples of HIT are electronic medical records, electronic health records (EHR) clinical decision support, RFID, mobile technologies, customer relationships management systems etc. (Furukawa et al., 2008; Tan et al., 2014).

Although HIT plays a critical role in delivering healthcare services, the investments in these technologies remain relatively low when compared to other sectors (Goldschmidt, 2005). There are frequent reports on resistance among healthcare professionals such as clinicians to use HIT despite the potential benefits (Romanow et al., 2012). For example, physicians at the Cedars-Sinai Medical Centre withdrew Computerized Physician Order Entry (CPOE) implementation as they considered the system to be a distraction to their medical routines. This is despite the fact that the system was already online in two-thirds

of the 870 hospital beds covered (Bhattacherjee and Hikmet, 2007). In a separate study by Venkatesh et al. (2011), it is also estimated that only one-third of all doctors use the technology solutions that are generally available to them (Venkatesh et al., 2011).

Although HIT has the potential to improve the operations of healthcare service providers, there is currently a lack of usage and an abandonment of systems. It is therefore critical for the healthcare industry to understand the factors that influence the acceptance and implementation of HIT. Venkatesh et al. (2012) emphasize that operations' literature would generally benefit from a better understanding of the acceptance of various technologies.

In this study, the HIT that is being examined is EHR. As defined by the Healthcare Information and Management Society and International Standards Organization, EHR is a longitudinal digital record of patients' healthcare information such as demographics and medical history; this repository of patient data is then stored digitally and exchanged in a securely and accessed by various authorized users. EHR is being identified as an important strategic IT that can move healthcare industry's values to the next level (Chong et al., 2015), and governments in countries such as Malaysia and the United States have identified investments in EHR implementations to be an important area of development in their national healthcare strategy (The Star, 2018). One of the key reasons why there is a low adoption rate of EHR in the healthcare industry could be attributed to the lack of training and support offered to the healthcare professionals (Venkatesh et al., 2011). Complicating this is the fact that the systems are often

introduced to healthcare professionals with little or no support and training, with the result that the adoption of EHR often takes a long time with no guarantee of achieving its intended benefits (Venkatesh et al., 2011). Even when healthcare providers have implemented EHR, the employees of the organizations often under-utilize the system, or fail to use the system as intended (O'Brien, 2008; Chong and Chan, 2012). An example includes nurses recording patient data manually, and only later transferring the data to the EHR (Chong et al., 2015). The current challenges in EHR implementation arise with the fact that although it is known to most that EHR can offer many benefits to healthcare organizations, many healthcare professionals are still not accepting of EHR. Some challenges include physicians finding the EHR systems burdensome, high costs of implementation and system interoperability issues (Forbes, 2019). Given these challenges, it is therefore critical to examine and understand the antecedents of success of EHR acceptance.

1.1 Information Technologies and Healthcare

Similar to many industries that are facing strong competition due to global competition, the healthcare industry is also constantly seeking ways to improve their operations and services to ensure that it stays current and can maintain its competitiveness (Chong et al., 2015). IT such as clinical information systems, patient tracking systems, e-health, RFID, EHR etc., are some key technologies that have been adopted by the healthcare industry in order for it to gain competitive advantages over other industries (Chong and Chan, 2012). With advancement in technologies such as those within the Internet, mobile data, big data and artificial intelligence, along with the increasing affordability of these

technologies, there are now more opportunities than ever to implement a wider range of IT in healthcare to improve operations, services to patients, as well as to increase the values offered by the healthcare industry. A key IT that has long touted to have the ability to transform the healthcare industry is EHR (Kohli and Tan, 2016).

How to implement EHR successfully in the healthcare industry has been a topic that has attracted the interests from both practitioners and researchers for some time (Simon et al., 2007, Cherry et al., 2008, Greenhalgh et al., 2010, Venkatesh et al., 2011). The implementation of EHR can provide better care and services to patients, and this includes diagnosis, test results, patient treatment, health monitoring, billing and the handling of patient care (Hossain et al., 2019). An overview of the EHR system is shown in Figure 1 below.

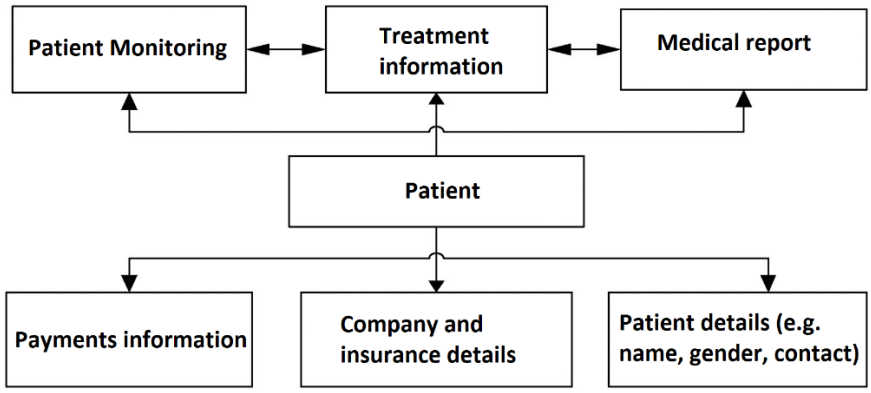


Figure 1.1 EHR system (Source: Hossain et al., 2019, pp. 77)

Although with the availability of current technologies as well as increasing affordability of IT, it is surprising that EHR implementation are still not being fully implemented across the healthcare sector. Given the benefits that EHR can offer, as well as the availability and affordability of the technology, it is

surprising that there are still barriers that are holding back the implementation of EHR by the healthcare industry. There are many places, especially in developing countries still using paper and cards to record patient information (Colligan et al., 2015). However, using conventional paper records of patient information has several drawbacks. Information on paper systems is sometimes incomplete, can contain ambiguous information, may not have a standardized format for the recording of data, lacks the ability to share the information across different hospitals, and is inefficient for searching and may have duplication of data (Hossain et al., 2019).

It is not a surprise that HIT such as EHR is touted as a key technology that can solve the issues found in paper-based systems (Kohli and Tan, 2016). Past studies have also shown that EHR can improve healthcare performance such as in decreasing the readmissions of chronic disease patients (Purtova, 2016). Despite the many advantages offered by EHR found in previous studies, the implementations of EHR remain low. Furthermore, there are also very limited studies investigating the factors that influence the success or failure of implementing EHR. Perhaps many of these studies were conducted at a time when the technology was still not so readily available, or had limited features (Venkatesh et al., 2011). Further complicating these deficits, many of these studies focused on patients' willingness to use EHR (Denton, 2011), or covered the topic from an organizational point of view (Chong and Chan, 2011), neglecting the relevant stakeholders of EHR at an individual level such as doctors, paraprofessionals and healthcare administrators (Chong et al., 2015).

1.2 Problem Formation

1.2.1 Current gaps in technology adoptions theories for EHR implementation

The study on the adoption of HIT and EHR by IS researchers has been on the rise in recent years (Wu et al., 2011, Chong et al., 2015). Many of these studies have focused heavily on the macro factors that influence the implementation of EHR (e.g. organization level and business environment) (Hung et al., 2010). In contrast, studies that examined the successful acceptance of HIT at the user levels, such as by doctors, paraprofessionals (e.g. nurses) and administrative personnel remain sparse. Understanding the acceptance of EHR at the individual level is critical as it is ultimately the individuals' decisions to accept and use EHR that determines the successful implementation of the system. Although there are studies that have examined the technical aspects of HIT such as issues related to systems integration (Yasnoff et al., 2004) and standards development (Raths, 2015), there is a lack of study on understanding the adoption of EHR from the healthcare professional's perspectives. Furthermore, in the relative few studies on users' healthcare related technology adoption, they are generally examined in a broader IS context (Venkatesh et al., 2011). Thus, existing studies on HIT adoption are mainly atheorectical and limited in terms of richness and scientific rigour (Venkatesh et al., 2011). In recent years, within the IS research community, there is a call for more researchers to contribute to transforming healthcare (Kohli and Tan, 2016), and EHR implementation is one of the key topics within these calls for more research work by the IS academic community. Based on the gaps in existing literature/studies where there is limited study on the acceptance of EHR at the individual levels of healthcare workers, theory-

driven research to understand the phenomena of the user and impact of EHR is much needed.

In order to understand what influences healthcare professionals' (i.e. doctors, paraprofessionals, administrators) decision to adopt and use EHR, there is a need to apply relevant theories to explain and examine their behavioural decisions. In the field of IS, scholars have regularly applied technology acceptance related theories in examining why users will accept or reject a new technology (Chong and Ooi, 2012). Some of the most common technology acceptance theories include technology acceptance model (TAM) (Davis, 1989), theory of planned behaviour (TPB) (Ajzen, 1991), Diffusion of Innovation theory (Rogers, 1995), and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). Among these, two of the most cited models include TAM and UTAUT. These two theories have been applied to a wide range of IS applications from mobile commerce (Chong et al., 2012; Chong, 2013; Chan and Chong, 2013), RFID in hospitals (Chong et al., 2015; Chong and Chan, 2012) and electronic medical records (Hennington et al. 2007).

Scholars have aimed to test the boundaries of the theories by examining the different IS applications in different countries (Al-Gahtani et al, 2012; Chong et al., 2012), different technologies (Venkatesh et al., 2011), and in different user personalities (Chong et al., 2015). In doing so, scholars have also extended these theories by either integrating different theories together (Zhou et al., 2010) and/or by adding new variables (Tan et al., 2014; Venkatesh and Davis, 2000). Although both TAM and UTAUT are among the most popular models in studying technology adoption, there is increasingly calls from the IS community

to state that perhaps research based on TAM has reached its theoretical limits (Benbasat and Barki, 2007). This is because TAM has been applied so extensively that there is little more to explore with TAM. There are even IS journals that state that they may not welcome research articles that simply just apply and extend TAM (i.e. Computers in Human Behaviour and Online Information Review). Unlike TAM, UTAUT is more recent and is considered a more comprehensive theory than TAM as it integrates eight existing technology adoption theories (i.e. Theory of reasoned action, TAM, the motivational model, the theory of planned behaviour, a model combining the technology acceptance model and the theory of planned behaviour, model of PC utilization, innovation diffusion theory, and social cognitive theory). Please refer to Venkatesh et al. (2003) for a detailed discussion of the theories that are integrated to form UTAUT.

However, Venkatesh and his colleagues recently stated that despite the wide application of UTAUT, there still exist some serious issues with many UTAUT studies (Venkatesh et al., 2016). Firstly, most scholars have not replicated the full UTAUT model in their studies, and they will usually only pick different variables and add them to UTAUT, or at times they may also remove some of the original variables in UTAUT, while still claiming to have applied UTAUT (e.g. Wong et al., 2015; Blut et al., 2016). Secondly, an important contribution of UTAUT is the moderators (e.g. age, gender, experience and voluntariness of use) proposed in the model. Yet most of the studies that applied UTAUT have excluded the moderators (Venkatesh et al., 2016), including some meta-analysis, which is meant to examine the generalizability of UTAUT (Taiwo and Downe,

2013). Despite the original UTAUT and many of Venkatesh's technology adoption studies that are conducted using longitudinal data (Venkatesh and Davis, 2010), most UTAUT studies have instead used cross-sectional data when testing the model. The challenge with using cross-sectional data is in that researchers assume that the predictors of UTAUT do not vary over time (e.g. pre-implementation versus post-implementation). Instead, many technology adoption studies found that the adoption factors will vary from pre-implementation to the full diffusion of a technology (Chong and Chan, 2012).

Lastly, this thesis also aims to include goal pursuit theory and team learning behaviour to extend existing technology adoption studies such as UTAUT. Although previous technology studies have placed much emphasis on the characteristics of technologies (e.g. compatibility) and users (e.g. innovativeness), most of these studies have neglected whether a user's motivation to pursuit a goal will influence his or her decision to use a new technology. Previous studies by Huang and Zhang (2011) and Zhang and Huang (2010) have shown that the attainment of the goal and velocity of achieving a goal both play an important part in influencing a user goal pursuit decision (e.g. learning and using a new technology). Despite testing the theories in various context such as blood donation and collecting stamps, there is very few studies that help us understand how goal pursuit theory can help us better understand a user's technology adoption decision. Furthermore, most technology adoption studies have placed great emphasis on individual user's technology decision without considering the role of team learning behaviour. In most organizations, a new technology introduced by the company will be used collective by a group

of employees rather than by an individual such as in the context of consumer technology (e.g. mobile phone). As such, it is important to consider the adoption decision beyond an individual's perspective, and take a broader view of whether individual will be influenced by how well his or her team members are also learning how to use the new technology.

Therefore, besides the gap in understanding what influence medical professionals' adoption of EHR, there is also a lack of proper testing or development of technology adoption theory in the area of EHR, creating an urgent need for the IS technology community to apply and improve the appropriate theory (e.g. UTAUT) to understand the factors that influence EHR adoption.

1.2 Justifications for selecting Malaysian healthcare industry

Malaysia is consistently ranked as having one of the best healthcare services in the world (The Sun Daily, 2017). The total healthcare spending in Malaysia was Ringgit Malaysia (RM) 52 Billion at the end of 2017, and it is forecasted to reach RM 80 billion by 2020 (The Sun Daily, 2017). The healthcare industry is also an important contribution to Malaysia's medical tourism industry (The Star, 2018). Medical tourism is expected to reach RM 2.8 billion in revenue by 2020 (The Star, 2018). As such, the Malaysian government has placed a great emphasis on ensuring that there are various strategic initiatives that can help to grow the healthcare sector. For example, eHealth is part of the key initiatives towards Malaysia's Multimedia Super Corridor (MSC) initiative. Despite these

initiatives, most of the digital initiatives in the Malaysia healthcare industry are not doing well. For example, it was acknowledged that only 20 percent of Malaysian hospitals currently have an electronic medical records system that can root out counterfeit drug issues (Healthcare Asia, 2018).

The current Malaysia health minister (i.e. Dr. Dzulfefly Ahmad) recently announced that Malaysia will implement EHR in 145 hospitals over the next three years from 2018 (Healthcare Asia 2018). The implementation of EHR will improve the healthcare services of Malaysia, but at the same time, it will also help address the challenges faced by the industry from other competing and neighbouring countries such as Thailand and Singapore (Popock and Phua, 2011). As Malaysia continues to place more emphasis and focus on medical tourism as a key contributor to its economic development, it needs to ensure that it can provide better and more affordable services when compared to healthcare providers in nearby regions such as Singapore and Thailand. As stated in the earlier section, EHR is able to improve the performance of healthcare providers, and as such offer competitive advantages to Malaysian hospitals and clinics over their competitors in other countries if they can be implemented successfully. Still, little is known in terms of what critical factors can influence healthcare professionals' successful acceptance of EHR. Smaller hospitals and clinics in Malaysia at times also question that given the financial investments required, and the low cost of administrators, whether EHR can really offer advantages over using a conventional paper-based system from a return on investment perspective. Therefore, it is of great importance to conduct research to help

understand factors that affect adoption, which will help healthcare providers to formulate better strategies for the successful implementation of EHR.

1.4 Research Questions and Research Objectives

With reference to the research problems discussed in the earlier section, the following research questions for this PhD study are proposed:

RQ1: Can UTAUT predict healthcare professionals' motivation to learn and the behavioural intention to adopt and accept EHR?

RQ2: Can UTAUT be extended to include goal attainment, perceived velocity and team learning behaviour to better predict healthcare professionals' motivation to learn and the behavioural intention to adopt and accept EHR?

RQ3: Is there a significant relationship between motivation to learn EHR and EHR behavioural intention to adoption and acceptance of EHR among Malaysian healthcare professionals?

Based on the research questions proposed, the following research objectives are developed:

1. To examine the relationships between UTAUT and the motivation to learn and the behavioral intention to adopt and acceptance of EHR among Malaysian healthcare professionals

2. To examine the relationships between the extended UTAUT (i.e. goal attainment, perceived velocity and team learning behavior) and the

motivation to learn and the behavioral intention to adopt and acceptance of EHR among Malaysian healthcare professionals

3. To investigate the relationship between motivation to learn EHR and EHR behavioral intention to adopt and acceptance of EHR among Malaysian healthcare professionals

4. To empirically test the proposed model in a longitudinal study among healthcare professionals in a medical group implementing the new EHR system.

1.5 Theoretical and Practical contributions of research

1.5.1 Theoretical contributions

There are several important contributions for this research. Firstly, this research proposed and tested a model that focused on EHR implementations in Malaysia. The topic on EHR has been gaining the attention of the government, scholarly community and healthcare industry. The medical industry has been identified as a key industry to the Malaysian government, and Malaysia's healthcare services have consistently being ranked as among the world's best. Despite this, medical clinics and hospitals that are key components of the healthcare industry, has not been a quick adopter to IS technologies when compared to its neighbouring peers such as Singapore and Thailand – two countries that are among Malaysia's competitors for the medical tourism sector. Despite the importance of the EHR system which can ensure that hospitals and clinics operate more efficiently, the

adoption of the system remains low. The medical group companies conducted in this study is among the largest group of private clinics in Malaysia, and yet until the recent two to three years, many of its clinics are still using paper-based systems in their operations. The importance of conducting research related to EHR is demonstrated by a recent call from Kohli and Tan (2016) which stated that IS researchers should pay more attention to EHR developments and investigate that research to understand how EHR can transform healthcare performance.

Secondly, this research examines how well UTAUT can be applied to understand medical professionals' behavioural intention to accept and use EHR. There have been questions by scholars on UTAUT's generalizability. Venkatesh et al. (2016) himself stated that scholars should apply different theories, and to apply UTAUT to different contexts to examine its generalizability. Despite UTAUT's popularity as it is of the most highly cited recent IS acceptance models, many studies that have claimed to have applied UTAUT have never really implemented the full UTAUT model. Previous studies have stated that although UTAUT is one of the most cited theories in the field of information systems, the theory has not been applied correctly, or the empirical tests of UTAUT are quite limited (Venkatesh et al., 2011; Venkatesh et al., 2016; Taiwo et al., 2013; Dwivedi et al., 2017). One of the key issues with existing UTAUT studies is that these studies only cherry pick a few UTAUT predictors (e.g. Wong et al., 2015; Blut et al., 2016) or they have neglected using the moderators proposed by UTAUT (e.g. Hew et al., 2015; Slade et al., 2015), which are important contributions of UTAUT. These issues have been confirmed by Venkatesh et al. (2016) in recent synthesis and review of UTAUT studies.

Context has always been recognized as an important boundary condition for the general application of theories. However, theories have only recently advocated for taking a more proactive approach in considering context in theory development (Venkatesh et al., 2011). In line with this, this study examines the generalizability of UTAUT as well as the extended UTAUT by testing them in the context of EHR adoption behaviour and use by Malaysia medical professionals. Theoretically, this thesis will examine the boundary limits of UTAUT, and investigate that in the context of different technologies and at different locations, should UTAUT be extended to better explain adoption behaviours?

Thirdly, previous studies have shown that UTAUT needs to be extended by integrating with other theories or predictors to better explain the technologies studied. For example, Chong and Ngai (2013) extended UTAUT with elaboration likelihood model (ELM) when studying travellers' decisions to adopt location-based social media for their travel planning. Zhou et al. (2010) similarly integrated UTAUT to explain mobile banking adoption. Venkatesh and his colleagues similarly extended their own original UTAUT by proposing the UTAUT2 when examining consumer related technologies (Venkatesh, et al, 2012). In this study, UTAUT is extended by integrating factors in goal pursuit theory such as perceived attainment and perceived velocity, as well as team learning behaviour. The significant contribution of this study is the development of the UTAUT extended model that examines the roles of perceived goal attainment, perceived velocity and team learning behaviour in understanding healthcare professionals' adoption and use decisions.

Fourth, this study addresses Maruping et al. (2017)'s arguments that there are limitations on using behavioural intention as a sole proximal determinant of IS adoption and use. In order to use IS, this study proposes that users' motivations should play a key role. Previous studies on technology adoption have examined the roles of extrinsic and intrinsic motivations. Intrinsic motivations such as perceived enjoyment and satisfactions has been examined by researchers such as Zhou (2010), Chong (2013), Venkatesh et al. (2012), Lacka and Chong (2016). Extrinsic motivations such as performance expectancy and rewards in technology acceptance have also been examined in studies such as Lee (2005), Teo (1999) and Yoo et al (2012).

Despite the extensive study on motivations, there is almost no study that examines the motivation to learn the technology. Users' level of motivation to learn the technology has often been neglected in IS adoption studies. Using an example to explain the importance of this issue: Although an employee may be forced to use a technology if it is being made mandatory by the company (Venkatesh et al., 2003), they may learn the technology per se, but may not have motivation to learn it, and rather are coerced to use the system. The result would be that they are merely using the basic features of the technology, or worst still, not using the technology correctly, resulting in the reduction of the overall organization's efficiency. An example would be employees keying in the data late rather than punctually (Venkatesh et al., 2011), which disrupts the business's operations. As such, this study includes the motivation to learn as well as the performance in using EHR. The theoretical basis of these is derived from goal attainment theory and have been studied extensively in the area of consumer behaviour by psychologists and marketing researchers. Although

Bagozzi et al. (1992) proposed a model that incorporated motivation to learn IT in technology acceptance, there have been few follow up studies to understand what influences the motivation of learning IT. Logically, users will need to learn how to use IS before using it. As an example, if users have not learnt python programming or they are not motivated to learn it, then it is unlikely that they will use python programming in their work. A factor that closely resembles this is learning goal orientation (Yi and Huang, 2003). Therefore, this study has extended UTAUT as well as technology adoption studies by proposing the link between the motivation to learn the system and the eventual acceptance of the system.

Lastly, similar to Venkatesh et al. (2011) and Venkatesh and Davis (2000), this study collected longitudinal data, and tested the original UTAUT as well as extended UTAUT model over 3 periods of time, namely; pre-implementation of the EHR system during the first month, the implementation stage during 2-3 month , and the post implementation stage during 4-5 month period. This is important as scholars have argued previously that technology acceptance studies should conduct longitudinal studies (Benbasat and Barki, 2007; Venkatesh et al., 2016) in order to see if the predictors of IS adoption and usage will perform consistently over time.

1.5.2 Practical Implications

This study has several important practical implications. Firstly, the study helps hospitals and clinics to understand how they can motivate their employees (i.e. doctors, nurses and administrators) to use EHR in their work. Understanding the important factors can help them to have better training, design better systems,

and provide the types of support that can help employees learn and use the system better.

Secondly, the healthcare industry is a key contributor to the Malaysian economy, and it has a long-term goal of having success in this sector through the growth of medical tourism, among other others. But in order to gain competitor advantage over other countries, the healthcare industry needs to operate more efficiently. This can be achieved not only through investing in EHR, but also in ensuring that the implementation of EHR is successful. The findings from this research will provide Malaysian healthcare organizations as well as the Malaysian government strategies to increase the adoption of EHR.

Thirdly, clinics and hospitals need to understand whether the factors that influence users' adoption and use of EHR will remain static or change over time. This will help inform clinics and hospitals management in terms of how they should develop their trainings and implementations plan to ensure that EHR will be adopted and used in the long term by healthcare professionals.

Lastly, clinics and hospitals can also use the results from this study to determine if they should have different types of training for different groups of users (e.g. gender, age, functional levels, etc.) in using EHR rather than having a one size fits all training programme. Training programmes can tailor to specific needs when planning for their training programme. Companies can highlight on the features (e.g. performance expectancy) or easiness to learn the system (e.g. effort

expectancy) to different groups. More support can also be provided for group that have slower velocity in learning EHR.

1.6 Overview of Methodology

This study adopts a two-step research design strategy, namely a 1) Pilot study, and 2) Main study.

1.6.1 Pilot Study

The pilot study involved developing a case with clinics in the Mediviron Group of companies which will help in identifying and confirming the variables developed from previous literature. During this stage, questionnaires will be checked with selected employees from the Mediviron Group of Clinics to ensure that the questions provided are clear and are measuring what they are intended to measure. One key goal of the pilot study is to help improve the clarity and relevant of the questions, and to refine the questions that will be used for the main study.

1.6.2 Main Study

The main study will be based in a survey. Working with the Mediviron Group of Companies, surveys will be distributed to more than 1500 employees in more than 200 clinics in the group. The data will be collected over a period of 6 months in 3 time props, ranging from pre-implementation (month 1), to

implementation (months 2-3) and sustained implementation (months 4-5). Three rounds of surveys will be distributed to the respondents over the 3 time periods.

1.6.3 Data Analysis

As the study is a survey-based study, descriptive statistics such as frequencies, percentage and means summarized the demographic variables of respondents to enable a better feel for the data and to provide guidance for conducting structural equation modelling (SEM) analysis. Reliability and validity tests will be conducted to test the measurement model. Finally, the conceptual models proposed in this research will be tested using the extended UTAUT.

1.7 Limitations of research

Despite the contributions of this study for both the theory and practice, there are several limitations. Firstly, the data from this study is collected from doctors, paraprofessionals, and administrators. It would be useful to conduct separate models that compare doctors, paraprofessionals and administrators' motivation to learn and accept EHR. Unfortunately, the sample size of this study is too small for the individual category of healthcare professionals to conduct comparison studies of different user groups. Secondly, this study is collected only from clinics from a large medical group. Although working with the medical group offers a great opportunity for this study to examine adoption of EHR systems from pre-implementation to a later stage of implementation via longitudinal study, there is a need to further examine the applicability of models proposed in this study. Thirdly, this study is conducted on a privately owned group of clinics. As such, the results may not be generalized to public hospitals and clinics.

Lastly, this study is conducted in Malaysia where there is a collectivist cultural environment. As such, the respondents may tendency to agree on the survey questionnaire regardless of the content of the questions, and this may present a chance of acquiescence bias in our data. Despite the limitations discussed, this study has provided compelling insights to help understand the adoption of EHR systems in Malaysia.

1.8 Summary of Chapter

This chapter provided an overview of the PhD thesis. Concepts related to EHR as well as technology adoption theories were discussed. The justifications to support why Malaysian healthcare industry was selected for this research were discussed. Research questions as well as research objectives were also provided. An overview of the methodology employed in this study was also presented. Lastly, both the theoretical and practical implications of this research were provided. In the next Chapter, literature related to EHR, as well as theories related to this thesis are discussed.

CHAPTER 2 LITERATURE REVIEW

2.0 Introduction

The purpose of this chapter is to review extant literature and to build a theoretical and conceptual framework on the related to the field of IS. This chapter presents an overview of Healthcare Information Technologies (HIT) and EHR. This is followed by discussions on HIT and EHR adoption in Malaysia. Since this chapter aims to find out the antecedents of EHR adoption and the theoretical foundation of these antecedents, previous studies related to the adoption of information technologies from both organizational technology and individual adoption theories are reviewed. The adoption theories that are examined here include Diffusion of Innovation, Technology-Organization-Environment Model, Theory of Planned Behaviour, TAM, and UTAUT. This research also examined Goal Pursuit Theories such as goal attainment and perceived velocity, and Work Team Learning in order to discuss how existing theories can be extended by these two theories.

2.1 Healthcare Information Technologies (HIT)

Healthcare spending amounts to a significant portion of the gross domestic product (GDP) in many countries, and governments, and healthcare leaders as well face challenges in managing healthcare spending and improving the quality of healthcare services (Chiasson, et al., 2007). In recent years, there is a growing focus on healthcare information system (HIS) as a solution to such problems.

HIT refers to information technologies that are applied to health and healthcare. HIT involves the application and exchange of information electronically in healthcare environments such as hospitals and clinics. They often include technologies such as computer hardware and software that 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 patient's electronic medical records, electronic health records (EHR), drugs and equipment inventories, hospital beds scheduling information, doctors' and nurses' working timetables and so forth, which are exchanged with the help of HIT (Chong et al., 2015). EHR allows healthcare professionals to access patients' health data within a robust digital system (LeRouge, et al., 2007); telemedicine and telehealth, the remote delivery of health care and health information between distant sites and participants (Bashshur, et al., 2000); and radio frequency identification (RFID), which can manage patients' medication and track patient drug-treatment compliance that results in better follow-up treatment (Wicks, et al., 2006). Mobile health services or mobile healthcare is also a technology worth mentioning, as it enables healthcare practitioners to have full time access to patients' clinical data (supported by EHR technology), and it provides novel opportunities for physician-patient joint decision-making and personalised healthcare.

There are various applications within HIT, and as classified by Furukawa et al. (2008), HIT can be categorized into technologies that help in prescribing or dispensing medicines. For technologies that support prescribing, they include

electronic health records (EHR), clinical decision support (CDS), and computerized physician order entry (CPOE). Applications for supporting dispensing medication include technologies such as bar coding or radio frequency identification (RFID), and automated dispensing machines. With the emergence of big data technologies and artificial intelligence (A.I.), other newer HIT includes the use of big data and A.I. for conducting predictive analytics, precision medicine and clinical decision support (Chawla and Davis, 2013).

In this thesis, it is not possible or practical to include all the HIT technologies in the study, given that these technologies have differing attributes. For example, the reason why hospitals may not adopt artificial intelligence could be due to the lack of technical know how, but this may be different from their reason for not using barcode technology. Instead, given the importance of EHR as well as to answer the call for various researchers such as Kohli and Tan (2016), this study will examine EHR, which is one of the most important HIT in healthcare organizations.

2.1.1 Electronic Health Record (EHR)

There are various definitions of EHR provided in the literature. The Healthcare and Management Society defines EHR as a longitudinal record of health information on patient that is produced by one or more encounters in any care delivering setting.

The Centre of Medicare and Medicaid Services defined EHR as an "*electronic version of a patient's medical history, that is maintained by the provider over time, and may include all of the key administrative clinical data relevant to that person's care under a particular provider, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports*" (Online Source: www.*CMS.gov* [accessed 24 April, 2019])

The Canada Health Infoway defines EHR as "*electronic health record (EHR) is a secure, integrated collection of a person's encounters with the health care system; it provides a comprehensive digital view of a patient's health history"* (Online Source: https://www.infoway-inforoute.ca [accessed 24 April, 2019])

All these definitions share the same key points, which is that EHR allows the sharing and storing of patients' information that are digitized, and the information is shared over time. With the use of EHR, healthcare professionals such as doctors and nurses can communicate well with each other as well as with their patients and improve safety in the healthcare organization where the environment is often fast paced and high reliability is demanded (Kohli and Tan, 2016). In most hospitals, EHR is developed once the healthcare organization implements automated transactional activities. Examples of these activities include the registration of patients, storing and ordering of clinical tests, and transferring the test information to the relevant healthcare professionals (Stead et al., 2009). By automating these processes, data related to patients' demographic information as well as the operational data of the healthcare

organization was also recorded. In many countries such as Singapore and Australia, such management of the data allow for the classification of diseases and are used to help treat diseases (Kohli and Tan, 2016). In many healthcare organizations, EHR that contain operations and patient data, are then shared between the relevant stakeholders in the healthcare organization to improve its efficiency and quality. As the healthcare industry faces the pressure of rising costs, many have viewed EHR as a technology that is capable of helping relevant stakeholders understand and contain costs, while at the same time helping to improve the quality of patient experience and care.

Successful implementations of EHR can have several benefits such as improvement in healthcare quality delivery, improvement in delivery efficiency, prevention of medical errors, reduction of the administrative workload, reduction of health care costs, and improvement in communication among healthcare professionals with their patients (Chong et al., 2015).

The adoption of EHRs can be traced back to when information systems were used to automate administrative processes, such as patient registration, orders and transmissions of clinical tests and test results. In the UK, what initially began as automated patient administration systems later developed into health information support systems and then resource management systems to manage patient transactions (Kohli & Tan, 2016). Henceforth, EHRs expanded to store comprehensive patient records in electronic format and cover “the entire continuum of a patient’s healthcare across institutions such as physician offices,

hospitals, diagnostics labs, and rehabilitation centres" (Kohli & Tan, 2016, p. 555).

While the adoption of EHR systems bring many potential capabilities, three particular functions have received much attention in improving the quality of healthcare and reducing costs: clinical decision support (CDS) tools, computerized physician order entry (CPOE) systems, and health information exchange (HIE). CDS systems primarily assist in making decisions with regard to patient care, for instance by providing the latest information about a drug or checking a patient's allergy to a medication (Menachemi & Collum, 2011). On the other hand, CPOE systems enable providers to input orders, such as for drugs and laboratory tests, into a computer rather than on paper (Menachemi & Collum, 2011). Providers is referred to hospitals, physicians, and other individuals who are involved in direct patient care, such as nurses and diagnostic technicians. Computerization not only decreases medical mistakes caused by human error, but also increases efficiency among staff. As for HIT, its function involves "the sharing of patient-level electronic health information between different organizations and can create much efficiency in the delivery of health care" (Menachemi & Collum, 2011, p. 48).

Despite the many benefits promised by EHR, there are still many challenges in the implementations of EHR in the healthcare industry.

One of the key challenges faced by healthcare organizations is the low adoption of EHR, which can be attributed to various reasons such as the resistance to

technology by 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 EHR is critical for the long-term success and growth of the industry.

While the goal of EHR is to make the delivery of healthcare services more efficient and effective, there are still challenges in its adoption and integration. For Kohli and Tan (2016), the obstacle for EHR's potential to be fully realised lies in the concerns among stakeholders. The authors classified these concerns into that of three groups of stakeholders – (1) patients; (2) providers; and (3) purveyors (Kohli and Tan, 2016). For patients, unauthorised disclosure and privacy of personal health records is a primary concern, which is a factor affecting patients' intention of using EHR. Moreover, some patients are concerned that the consolidation of EHRs may lead to changes in treatment that work for them if authorities found such treatment to be less effective for other patients (Kohli & Tan, 2016).

For providers there is concern with the connectivity of disparate systems, completeness and maintenance of health records. Inaccuracy of EHRs may cause providers to miss vital clues when treating patients. In addition, organisational issues such as differences in EHR standards and delays in sharing data with other providers are also concerns for this group of stakeholders (Kohli

& Tan, 2016). For purveyors, as their role is deal with the inter-organisational use of EHRs for analytics and research, their primary concerns include the lack of data exchange standards, incompatibility in interfaces, data latency and unauthorised access across different sectors of healthcare provision (Kohli & Tan, 2016).

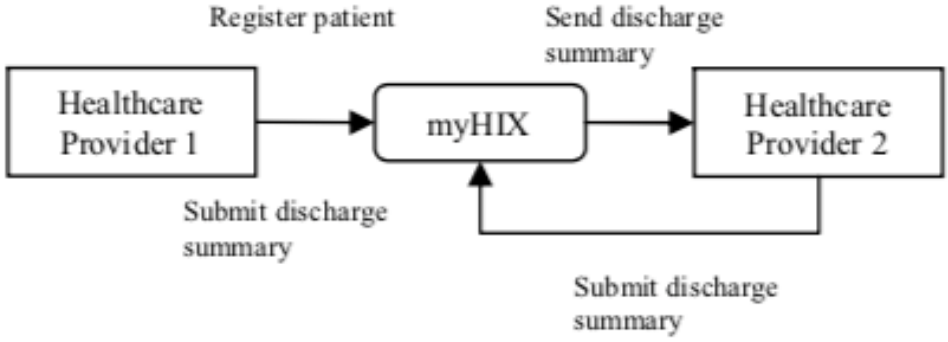
2.2 EHR and HIT adoption in Malaysia

As many countries are taking initiatives to adopt and implement EHR into their public health system, Malaysia is also finding it the best approach to do so. In 2000, the Ministry of Health Malaysia (MOHM) implemented a telehealth flagship project, under which four pilot projects were developed, namely the Mass Customised/Personalised Health Information and Education (MCPHIE); Continuing Medical Education (CME); Teleconsultation; and the Lifetime Health Plan (LHP) (Som, et al., 2010). The MOHM later restructured the plan to include Lifetime Health Record (LHR), which is a summary of an individual's health record throughout his or her lifetime, with information accumulated since his or her first use of the LHR (Som, et al., 2010).

According to Som et al. (2010), in 2002, there were only four hospitals that ran the Clinical Support System (CSS), which is a sub-application required for the implementation of LHP. CSS consists of key components such as Hospital Information System (HIS), Clinical Information System (CIS) and Pharmacy Information System (PIS) that recorded health information specific to a patient. Based on a survey conducted by Ghani et al. (2008) in year 2006, patient medical

records are paper-based and stored in the records office at each health facility. In the same study, Ghani et al. (2008) concluded that EMR, or clinical application system was given less focus for collecting and generating the LHR, as the majority of the systems were still under trial at the time of the research (Ghani, et al., 2008).

However, there was a gradual improvement in adoption as 17 hospitals implemented such applications in 2010 (Som, et al., 2010). Hospital Selayang became the first paperless and filmless hospital, deploying HIS (Som, et al., 2010). Another noteworthy initiative is the Malaysian Health Information Exchange (MyHiX) introduced by MOHM in cooperation with Multimedia Development Corporation (MDeC) in 2009. As shown in Figure 2.1 and according to Som et al. (2010), MyHiX is aimed to record all clinical summaries of a patient electronically when he or she is discharged by healthcare providers to ensure the continuity of care for the patient. MyHiX also facilitates the exchange of these records between government hospitals or clinics, and the data flows thorough an online virtual private network (Ismail & Abdullah, 2017). Not only does the system have the potential to provide continual and better-quality healthcare to patients, it allows for the constant update of patients' LHRs in government healthcare facilities. Nevertheless, out of 139 public hospitals and 2839 public clinics in Malaysia (as of 2017), only eight Malaysian healthcare institutions have implemented MyHiX (Ismail & Abdullah, 2017).



(Source: Som et al., 2010, pp. 662)

Figure 2.1 Overview of myHIX principle of operation

According to Ghani et al. (2008), the lack of standards in collecting and sharing health information hinders collaboration among healthcare organisations, thus affecting the interoperability of clinical information. Further, integration issues on health ICT are a key challenge for the successful implementation of EHR. According to Ghani et al. (2008), uncoordinated planning coupled with outdated systems that are limited to little or no networking capabilities are factors that cause such integration issues. Ghani et al. (2008, p. 90) further highlight the challenges for system integration:

"*The integration challenges include a health informatics standard (such as a clinical code set, e.g., clinical terminology, drug code, disease code classification, and administration code set, e.g., health facility code and demographic code), an information system architectural standard (such as software, hardware, operating system, middleware, network communication protocol, database system, data model and information communication protocol) and standard operating procedures (such as care pathways, clinical professional guidelines and operational policies)*." (Ghani et al.. 2008, pp. 90)

Looking specifically at the implementation of MyHiX, Ismail and Abdullah (2017) argued that budget constraints in the development in the infrastructure and system was an issue. The authors also resonate similar arguments by Ghani et al. (2008) in that the MyHiX did not achieve the desired interoperability, which has resulted in difficulties in sharing patient and healthcare information across providers.

As shown in the discussions, there is abundant attention being paid to examine the implementation of HIT in Malaysia from the technical perspectives. There is however a paucity of research examining the barriers towards HIT implementation in Malaysia from the perspectives of the users (Chong et al., 2015). Although EHR implementation faces some of the technical challenges discussed (e.g. data standardization issues), the focus of this research is to examine the factors that will influence users to successfully accept and use EHR, which is also key to ensure the technology takes off successfully in the healthcare industry.

2.3 Technology acceptance theories

Previous IS acceptance studies have used various relevant theories to understand the factors that lead to the successful adoption of IS, such as Technology Acceptance Model (TAM), Diffusion of Innovation (DOI) (Rogers, 2010), Technology Organization Environment (TOE) (Wang et al., 2010) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al.,

2003). In the area of healthcare related technologies, IS scholars applied these models in understanding the adoption of IS technologies in the healthcare industry such as RFID (Chong and Zhou, 2014), healthcare information systems (Pai and Huang, 2011), and electronic logistics information systems, (Tung et al., 2008) to name a few. The adoption of EHR are conducted from various perspectives, namely from the perspective of organizations, as well as in the context of individual users such as patients, or healthcare professionals such as doctors (Chong et al., 2015). In the context of organizational adoption research, some of the most common theories include Innovation Diffusion Theory (Rogers, 1995), and Technology-Organizational-Environmental Model (Tornatzky and Fleischer, 1990). In terms of theories that are applied to users' acceptance of technologies, some of the most widely cited theories are Theory of Planned Behaviour (TPB), Privacy Calculus Model, Status Quo Bias Theory, Task Technology Fit, Expectations Confirmation Model, Delone and Mc-Lean framework, TAM and UTAUT. TAM has in the past been extended to TAM2 and TAM3 while UTAUT was also extended to UTAUT2 to examine consumer technologies as opposed to work-based IS.

2.3.1 Organizational technology adoption theories

Although information technologies can offer competitive advantages to many organizations, there are times when organizations do not adopt these technologies. The reasons for these vary, ranging from issues related to cost, trust, to top management support (Chong et al., 2009). In general, the predictors of organizations' adoption of technologies can be grouped into environmental,

organizational or technological factors. Past studies that have examined the adoption of technologies from the perspectives of organizations have used Diffusion of Innovation Theories and Technology-Organization-Environment (TOE) model as their theoretical foundation. The next section provides the discussions of these two theories.

2.3.1.1 Diffusion of Innovation Theories

In examining existing technology adoption literature including HIT and EHR, it is found that one of the most popular models that was applied is Roger's Diffusion of Innovation Theory. Rogers (1995) defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system" (p. 5). In DOI, it is stated that individuals are viewed as having varying degree of willingness to accept and use an innovation, and therefore it is usually observed that the portion of the population accepting an innovation will be distributed normally over time (Rogers, 1995). When examining the distribution and breaking it into segments, it will show that individuals can be separated into five categories of individual innovativeness ranging from the earliest adopter until the latest adopter (Rogers, 1995). These five segments are categorized as innovators, early adopters, early majority, late majority, and laggards (Rogers, 1995). Table 2.1 below provides a summary of the characteristics that present each of these five categories of individuals.

Table 2.1 Characteristics of individual innovativeness (Rogers, 1995, pp. 50)

Category	**Descriptions**
Innovator	Educated, adventurous, and willing to seek for various information
Early adopter	Educated, take leads in social group, adored by others
Early majority	Deliberate, and have good network which are developed through informal contacts
Late majority	Tend to be more conservation, and come from less well off social economic group, tend to be sceptical
Laggards	Worry about debts, will only seek information from close network such as friends, relatives, and neighbours

.

The adoption distribution curve can be converted into a S curve that is generated to show the rate of innovation adoption among the population (Rogers, 1995). The rate of innovation adoption in turn is affected by five perceived attributes of innovations.

The five perceived attributes of an innovation determining the rate of adoption identified by Rogers (1995) are: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage is defined as the degree to which an innovation is perceived as being better than the idea it supersedes. Compatibility is defined as the degree to which an innovation is perceived as consistent with existing values, past experience, and needs of potential adopters. Complexity is defined as the degrees to which an innovation is perceived as relatively difficult to understand and use. Trialability is defined as the degree to

which an innovation may be experimented with on a limited basis. Observability is defined as the degree to which the results of an innovation are visible to others.

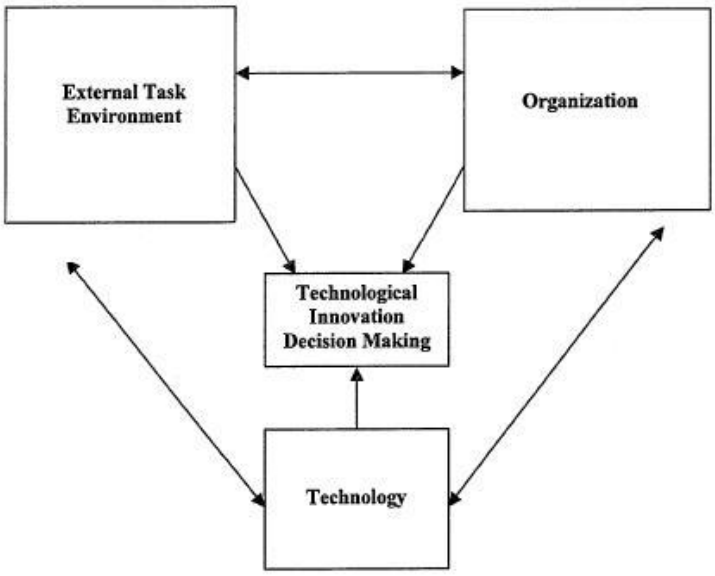
Although Diffusion of Innovation theory can explain to some degree why organizations adopt technologies, the theory itself is not sufficient to capture all the factors that influence the adoption of EHR (Chong and Chan, 2012). First, Diffusion of Innovation theory only examines organizations' decision to adopt technology based solely on technological attributes. The theory itself neglects other factors related to the external environment (e.g. competitive pressure) and organizations (e.g. organization structure and technical competency of staff). Second, despite proposing a five-stage adoption process consisting of knowledge, persuasion, decision, implementation, and confirmation phases, most study have ignore the implementation stages of the model. Lastly, the model only focuses on the adoption of technology from an organization's macro view, and neglects the roles individual users play in the organizations. Therefore, in many studies such as those by Chong and Chan (2012), Chong et al. (2015) and Alaiad and Zhou (2017), additional factors and theories are often being used to explain the adoption of EHR from the organization's perspective.

2.3.1.2. Technology-Organization-Environment Model (TOE)

The TOE framework proposes that three aspects of an organization's context influence technology adoption: the technological, organizational, and environmental (Tornatzky and Fleischer 1990). The technological context describes the characteristics of existing and new technologies that are important to the organization. The organizational context describes the characteristics of

organizations in light of factors such as age, scope, and size. Lastly, the environmental context describes the external arena in which an organization operates.

The TOE framework is very profound in the IS literature and has been applied in various study contexts. Wei et al. (2015) and Wang et al. (2010) draw upon the TOE framework to investigate the determinants of RFID assimilation and adoption in China and Taiwan respectively. The framework was also used to investigate discontinuance intentions of technology (Furneaux and Wade 2011). Zhu and Kraemer (2005) and Zhu et al. (2006) explore the roles of TOE factors in the assimilation of e-business in varying settings. Kuan and Chau (2001) use the framework in investigating the adoption of EDI in small businesses, while Chau and Tam (1997) focused on the adoption of open systems. Even earlier literatures such as Iacovou et al. (1995) developed a TOE framework consistent with Tornatzky and Fleischer (1990) and examined it using case studies. Figure 2.2 provides an overview of the TOE model.



(Source: Tornatzky and Fleischer, 1990, pp. 50).

Figure 2.2 Technology-Organizational-Environmental Model

Although TOE has been applied in studying healthcare technologies such as those by Sulaiman, and Magaireah (2014), there remain some challenges in applying TOE to the context of this study. Firstly, although TOE model proposed by Tornatzky and Fleischer (1990) contains variables shown in Figure 2.2, many subsequent studies claiming to have adopted TOE have included different variables under the TOE header. As such, TOE has become more of a framework than a theory whereby researchers group their variables under the separate technology, organizational, and environment headings. For example, in studying e-health record adoption in Jordan healthcare organizations, Sulaiman and Magaireah (2014) applied TOE and used technological contexts such as security, privacy and reliability. Chong and Chan (2014) in studying RFID adoption in the healthcare industry, used technological factors related to DOI

such as relative advantage, complexity and compatibility in their TOE model. Chan and Chong (2013), in examining mobile supply chain management diffusion, applied TOE where the environmental factors include competitive pressure and expectations of market trends. Therefore, most studies on TOE are no longer applying TOE model, and instead, are using TOE as a framework to categorize variables into various perspectives: Technology, Organizational, Environment.

Secondly, due to the first point where TOE is being used as a framework and include different variables under the TOE framework, authors have applied a piece meal approach and picking partial variables from different theories such as TAM and DOI (Gangwar et al., 2015). This limits the ability to test the actual TOE model as well as generalizing the theory to different contexts. At times authors do not apply the theories in a rigorous manner, resulting in overlapping variables within the model. For example, in Gangwar et al. (2015), both perceived that usefulness and relative advantage are used in their research model, when both variables essentially measure the same thing. Thus, there is confusion among authors who applied TOE with some including variables from theories such as DOI or TAM in one of the TOE's dimensions (e.g. Low et al., 2011), while others claimed to have extended TOE with DOI or TAM such as those conducted by Gangwar et al. (2015).

Lastly, this theory, i.e., TOE is more suitable when studying the adoption from the perspective of organizations. In this tudy, given that the key focus is related

to individual user's technology adoption decisions, TOE is therefore not an appropriate theory to be applied to the context of this research.

A review of technology adoption past studies that have applied the TOE model is shown in Table 2.2, and the summary of the variables used.

Table 2.2 Summary of TOE studies

Paper	**Technology Studied**	**TOE variables**
Chong and Chan (2014)	Healthcare RFID	Technology: Relative Advantage, Compatibility, Complexity, Cost, Security Organizational: Top Management Support, Organization Size, Financial Resources, Technological Knowledge Environment: Competitive Pressure, Expectations of Market Trend
Chan and Chong (2013)	Mobile SCM	Technology: Expected Benefits, Complexity, Perceived Cost, Security and Privacy, Technology Integration Organizational: Top Management Support, Organization Size, Financial Resources, Technological Competency Environment: Competitive Pressure, Expectations of Market Trend
Chan et al. (2012)	E-collaboration	Technology: Technological Integration, Performance Expectancy, Effort Expectancy Organizational: Technology Readiness, Managerial obstacles Environment: Global scope, Competitive Pressure Market Trends Expectations
Kuan and Chau (2001)	EDI	Technology: Perceived direct benefits, perceived indirect benefits Organization: Perceived financial cost, perceived technical competence Environment: Perceived industry pressure, perceived government pressure
Xu et al. (2004)	E- business	Technology: Technology competence Organization: Firm size, global scope, enterprise integration Environment: Competition intensity, regulatory environment Technology: Perceived benefits, perceived cost
Gibbs and Kraemer (2004)	E-commerce	Technology: Technological Resources Organizational: Perceived benefits, Compatability, Financial Resources, Firm size

		Environment: External pressure, Regulations, Government Support
Chau and Tam (1997)	Open Systems	Technology: Perceived benefits, Perceived Barriers, Compliance to Standards' importance, Interconnectivity, Interoperability Organizational: Complexity, Satisfaction with Current System, Team Formalization Environment: Market Uncertainty
Awa et al. (2016)	ERP	Technology: Technical Know How, Compatibility, Perceived Values, Security, ICT Infrastructure Organizational: Firm Size, Subjective Norms, Scope of Business Operations, Demographic Compositions Environment: External Support, Competitive Pressure, Partners' Readiness
Low et al. (2011)	Cloud Computing	Technology: Relative Advantage, Complexity, Compatibility Organizational: Top Management Support, Firm Size, Technology Readiness Environment: Competitive Pressure, Trading Partner Pressure
Hart et al. (2015)	E-commerce	Technology: Perceived Usefulness, Perceived Ease of Use, Perceived Behavioral Control, Perceived Service Quality Organizational: Business Operations' Scope, Firm Size, Firm Missions, Facilitating Conditions, Individual Differences, Social Influence Environment: Consumer Readiness, Competitive Trading Partner Readiness, Perceived Trust
Gangwar et al. (2015)	Cloud Computing	Technology: Relative Advantage, Compatibility, Complexity Organizational: Organization competency, Training and Education Level, Top Management Support Environment: Competitive Pressure Market, Trading Partner
Sulaiman and Magaireah (2014)	e-Healthcare Record	Technology: Privacy, Security, Reliability Organizational: Technological Readiness, Top Management Support Environment: Competition, Legal Environment, Government Policy

2.3.2 Individual technology adoption theories

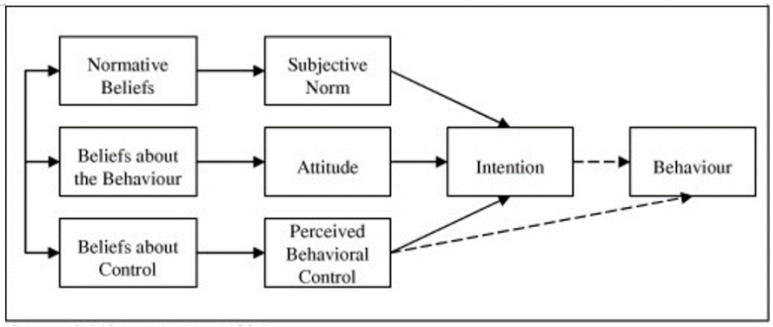
Understanding why individuals accept and use information systems has been one of the key research areas for Information Systems (IS) scholars over the last few decades (Wu and Lederer 2009). Several theoretical models, such as the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB), have been employed by researchers to understand the motivations of individuals to accept and use new information technologies (IT). Among the many theories, the Unified Theory of Acceptance and Use of Technology (UTAUT) remains as one of the most often cited and widely applied IS theories. The next section provides a review of these theories.

2.3.2.1 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) is built upon the Theory of Reasoned Action (TRA) and extends it by adding perceived behavioural control. According to TPB, a person's actual behaviour is directly influenced by his or her behavioural intention and in turn jointly determined by attitudes, subjective norms and perceived behavioural control toward performing the behaviour (Ajzen 1991).

TRA (Fishbein & Ajzen, 1975) examines situations where users have no complete control over their choices, but are somehow conditioned by non-motivating factors related to the availability of certain requirements and resources (Fishbein and Ajzen, 1975). Similar to TRA, the Theory of Planned

Behaviour views intention as the best behaviour indicator. This is because it shows the efforts that a user is willing to go to in order to perform a specific action (Ajzen, 1991). As stated earlier, TPB's main three variables which predicts behavioural intentions are attitude, subjective norm and perceived behavioural control (See Figure 2.3)



(Source: Schiften and Ajzen, 1985, Web: https://is.theorizeit.org/wiki/Theory_of_planned_behavior [accessed: 24 April 2019])

Figure 2.3 Theory of planned behaviour.

The attitude towards the behaviour is the global predisposition for developing this behaviour. Fishbein and Ajzen (1974)'s proposed expectations-value model stated that a user's attitude is determined by his or her beliefs regarding behaviour and the eventual consequences, and the importance to which they are given. Subjective norm however, refers to how a user is influenced by the perceptions of someone who is significant to them, such as a family member or friend (Fishbein & Ajzen, 1973). Subjective norm is influenced by both the normative beliefs of the user associates with significant referents and the motivation to behave accordingly to their wishes (e.g. peer pressure). Lastly,

perceived behavioural control refers to whether a user's perception of the available or lack of the necessary resources and opportunities to develop this behaviour. Therefore, perceived control is influenced by the individual beliefs on factors determining behaviour and from control over such factors.

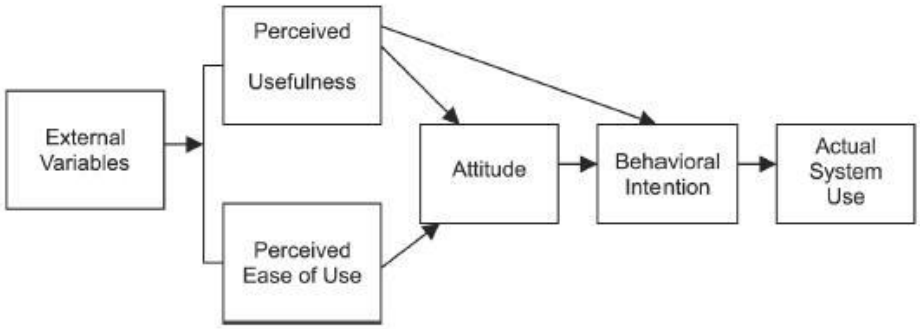
Based on TPB, a user's attitude, subjective norm and perceived behavioural control are the reasons to explain an individual's actions. TPB also posits that perceived control has a direct influence on a person's effective behaviour. Therefore perceived control can indicate a person's effective capacity to perform an action as far as the individual's beliefs represent the real limitations it has to face. TPB has been combined with theories such as TAM and UTAUT to examine various IS technologies' acceptance and use (e.g., Pavlou and Fygenson 2006; Lu et al. 2009; Shih and Fang 2004).

2.3.2.2 TAM

TAM is derived from Theory of Reasoned Action (Arjzen and Fishbein, 1980). TAM was developed to predict the factors that influence an individual's adoption and use of an IS. TAM remains as one of the most popular models to understand an individual's decision to adopt new technology, and as of January 2019, the two papers that introduced TAM, i.e. Davis (1989) and Davis et al. (1989), based on Google Scholar citations, stand at 42140, and 21587, respectively.

TAM believes that both usefulness and ease of use are always the primary determinants of IT/IS adoption in organizations. These two determinants serve as the basis for attitudes toward using a particular system, which in turn determines the intention to use, and then generates the actual usage behaviour.

Perceived ease of use is the extent to which a person believes using the system would be free of mental effort (Davis, 1989). One of the key purposes of TAM is to provide a basis for discovering the impact of external variables on internal beliefs, attitudes, and intentions. The model of TAM is shown in Figure 2.4.



(Source: Legris et al., 2003, pp. 193)

Figure 2.4 Technology Acceptance Model (TAM)

TAM has received extensive empirical support through validations, applications, and replications for its power to predict use of Information Systems (Lu, et al., 2003; Perez et al., 2004; Fusilier and Durlabhji, 2005). However, researchers also found that the generality of TAM fails to provide more meaningful information on users' opinions about a specific system (Lu, et al., 2003). As such, there is a need to incorporate TAM with additional factors or integrate it with

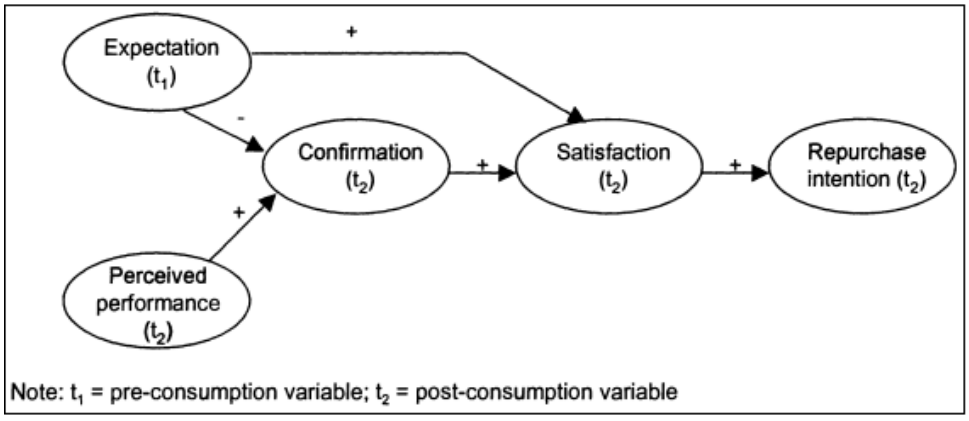
other IT acceptance models for improvement of its specificity and explanatory utility. There have been researchers in the past who tried to add additional factors to technology acceptance model. For example, a model of consumer trust was developed to explain consumer trust in an Internet-based store (Jarvenpaa et al., 2000). The trust factors are perceived size, that is the store's size from customer's perception, and perceived reputation, that is the store's reputation from customer's perception. Vijayasarathy (2004) introduced an augmented TAM to predict consumer intentions to use online shopping. New variables in the model are privacy, which is the degree to which personal information is protected and security, defined as "the extent to which a consumer believes that making payments online is secure" (pp. 37). Heijden et al. (2003) also extended the TAM model when they study the consumer intentions to use online purchasing. The conceptual framework includes trust in the online store, perceived risk, perceived usefulness, perceived ease of use, attitude towards online purchasing, and online purchase intention.

2.3.2.3 Expectations Confirmation Theory in IS

Although earlier theories such as TAM and DOI provided theoretical understanding of why users adopt IS, Bhattacherjee (2001) correctly argued that while initial acceptance of an IS is an important first step to an organization's IT implementation success, its long-term viability eventual success will ultimately be based on continued use. As stated by Bhattacherjee, the concept of continued use has also been examined by IS scholars in various other ways such as post implementation (Nicolaou, 2004), Diffusion (Chong and Chan,

2012), assimilation (Zhu et al., 2006) etc. The common theme central to these studies is the acknowledgement that after the initial adoption stage, there is a post acceptance stage when the use of IS transcends into a conscious behaviour and becomes part of a normal routine activity (Bhattacherjee, 2001).

Bhattacherjee (2001)'s expectations confirmation model in IS (ECM-IS) is one of the key papers that examines a theory that differentiates between a user's decision to accept an IS and the continuance behaviour. The key theoretical underpinning of the ECM-IS is from the expectation-confirmation theory (ECT) (Oliver, 1980).



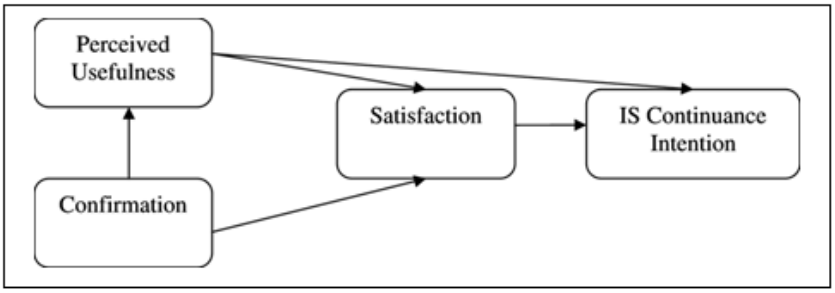
(Source: Bhattacherjee, 2001, pp. 353)

Figure 2.5 Expectations Confirmation Model

Figure 2.5 presents the main constructs and relationships in a traditional ECT. As the figure shows, a customer will first form an initial expectation towards the specific product or service before he or she purchases. The customer will then adopt and use the specific product or service. After a period from the initial use of the product or services, the customer will form a perception about the products1 or services' performance. This will lead to a comparison between the perceived performance with the original expectations and determine the extent

which this initial expectation is confirmed. Once this happens, a customer will experience satisfaction based on whether his or her earlier expectation is confirmed. This will lead to a re-purchase intention from a satisfied customer, while a dissatisfied customer will discontinue use of the goods and services.

The ECM-IS model is similar with ECT since an IS user's continuance decision is quite similar to a consumer's re-purchase decision. This is because in both models, the IS user and consumer will both make their decisions based on an initial (i.e. acceptance or purchase) decision; are influenced by the initial use experience; and can lead to an ex-post reversal of the initial decision (Bhattercherjee, 2001).But given that the two models' contexts are different, Bhattercherjee (2001) adapted ECT by integrating it with TAM. Unlike ECT, ECM-IS focuses only on the post-acceptance variable. ECM-IS also includes an ex-post expectation which was not proposed in ECT. Lastly, the ex-post expectation in ECM-IS is measured by perceived usefulness. ECM-IS is shown in Figure 2.6.



(Source: Bhattacherjee, 2001, pp. 356)

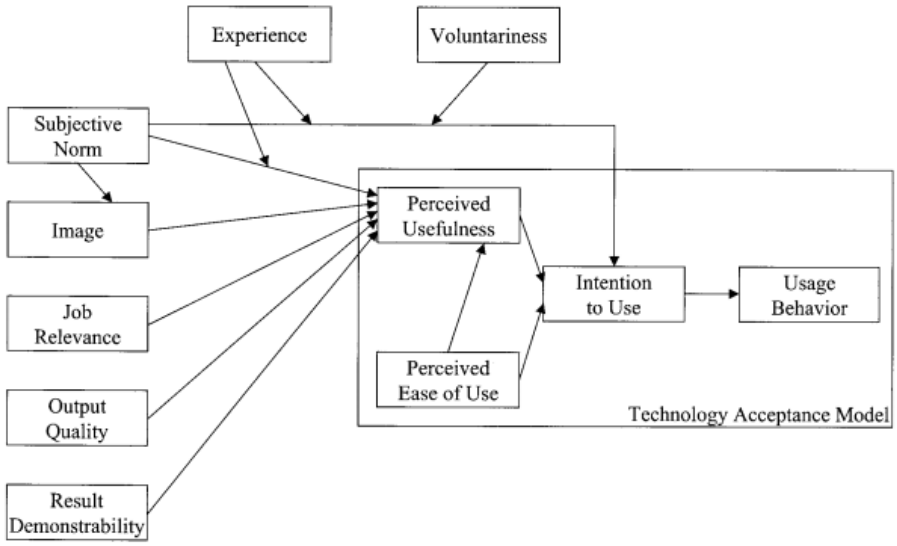
Figure 2.6 Expectations Confirmation Model in IS

The ECM-IS model has been applied and extended in various technology acceptance and post-acceptance studies since it was introduced in 2001. For example, Thong et al. (2006) applied ECM-IS by expanding post-adoption belief in studying continuance of use of IT. Their studies tested and confirmed that besides perceived usefulness, perceived enjoyment and perceived ease of use can influence user satisfaction and continued IT usage. Lin et al. (2005) on the other hand, added perceived playfulness in ECM-IS when studying users' continued use of websites. Chong (2013), in studying the continuance intention to use mobile commerce, added trust and perceived cost as the ex-post expectations of users.

The main contributions of ECM-IS in studying IS adoption is how the model focuses beyond just a single stage of initial adoption, and instead looks at the post-adoption decision of continuance intentions. Thus the adoption decision of a user is not viewed as just one static decision, but instead may change over a course of a user's product use lifecycle. One key limitation of the model and in later studies is that the model and extended models do not measure the changes in variables such as perceived usefulness or perceived ease of use over time (Chong ,2013). For example, although a user may find the perceived ease of use to be an important predictor of continuance intention use, but as the user becomes more experience with the IS, it is possible that the role of perceived ease of use in affecting user continuance use decision decreases. This gap in the current model leads to opportunities for IS adoption studies that collect and test longitudinal data and examine how the antecedents of technology adoption changes over time (Zhang et al., 2014).

2.3.2.4 TAM 2 and TAM 3

Researchers have later extended TAM into TAM2 (Venkatesh and Davis, 2000) and TAM3 (Venkatesh and Bala, 2008). Using TAM as a base model, Venkatesh and Davis (2000) extended TAM by incorporating additional variables that are important to help understand the determinants of perceived usefulness, and included social influence processes such as subjective norm and image, as well as cognitive instrumental processes such as job relevance, output quality, result demonstrability and perceived ease of use and voluntariness. Figure 2.7 below shows the proposed TAM2 by Venkatesh and Davis (2000).



(Source: Venkatesh and Davis, 2000, pp. 188)

Figure 2.7 Technology Acceptance Model 2

TAM2 offers greater insights than TAM as it is now agreed by most scholars that perceived usefulness and perceived ease of use in general have an influence on user intention to use a new technology (Benbasat and Barki, 2007). The key

antecedents of perceived usefulness proposed in TAM2 are derived from three theoretical paradigms, which are work motivation theory, action identification theory and behavioural decision theory. Venkatesh and Davis (2000) stated that an individual's perception formation on perceived usefulness are based on an instrumental process. They argued that the underlying role of cognitive instrumental process is that an individual will form his or her judgement on perceived usefulness by cognitively comparing the capability of an IT system with what they need to do in their job. Thus, TAM2 posits that the perception of an IT's perceived usefulness will be based on a user's mental assessment of the match between the work goals with the consequences of performing a job task using an IT.

The antecedents of perceived usefulness in TAM2 are explained in detail here. Subjective norm is one of the original variables used in Theory of Reason Action (TRA), where the role of social influence is measured via subjective norm. Subjective norm is defined as a person's perception of whether the people who are important to him or her think that this person should or should not perform the behaviour in question (Fishbein and Ajzen, 1975). Image in the model is defined as "the degree to which use of an innovation is perceived to enhance one's status in one's social system" (Venkatesh and Davis, 2000, pp. 189). Job relevance is defined in TAM2 as whether the systems in use is relevant to his or her job. That means job relevance measures the importance within one's job of the set of tasks the IT is capable of supporting. TAM2 also explains that besides examining what tasks a system is capable of performing and the degree to which those tasks fits into their job relevance, users of an IT system will also take into

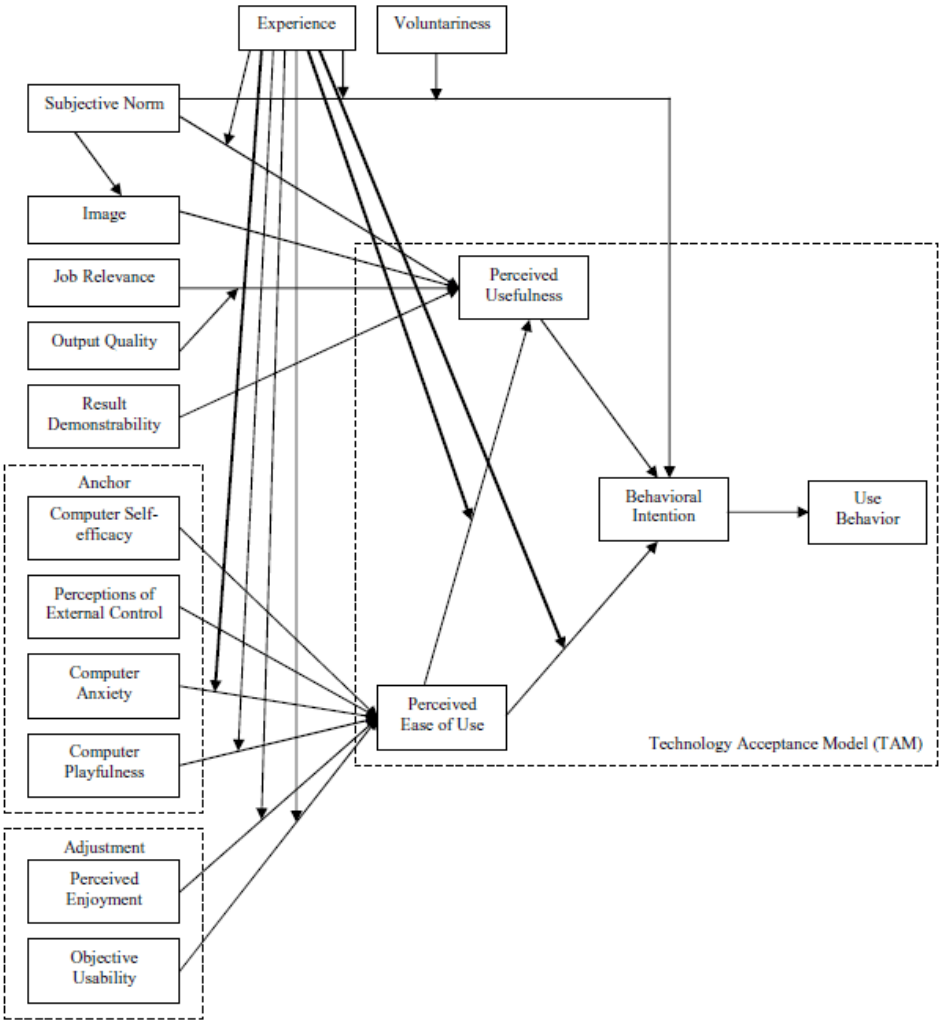
consideration how well the IT performs those tasks, which aims to measure output quality. Lastly, result demonstrability in TAM2 looks at the tangible results derived from using the IT system. Another extension of TAM2 over TAM is the two moderators that are proposed: experience and voluntariness. Experience refers to a user's previous computer experience, and voluntariness refers to whether an IT usage is made compulsory by the company.

The TAM2 model was applied to examine four different studies by Venkatesh and Davis (2000) which include a manufacturing site employing a proprietary system, a large financial services firm which is migrating from its mainframe system to a Windows based environment, a small accounting firm which bought a new Windows based customer account management system, and an investment bank implementing a new stock management system. The results from Venkatesh and Davis (2000) confirm the variables proposed in TAM2. Factors such as subjective norm, image, job relevance, output quality and demonstrability were found to be predictors of perceived usefulness. Experience was found to moderate the relationships between subjective norm and perceived usefulness, and subjective norm and intention to use. Voluntariness on the other hand, was found to moderate the relationship between subjective norm and intention to use.

TAM3 was subsequently proposed by Venkatesh and Bala (2008) to examine the determinants of perceived ease of use such as computer self-efficacy, perceived enjoyment, and computer anxiety, to name a few. This is different from TAM2 were the determinants of perceived usefulness was examined.

TAM3's theoretical underpinning is derived from the anchoring and adjustment framing of human decision-making. Combining with variables from TAM2, TAM3 further proposes anchoring factors which are computer self-efficacy, perception of external control, computer anxiety, computer playfulness; and adjustment factors which have perceived enjoyment, and objective usability as predictors of perceived usefulness.

Computer self-efficacy is defined as the degree which a user believes he or she has the ability to learn the IS to perform the required tasks. Perception of self-control is the degree which the user believes there is technical and organizational resources that will support the use of the IS. Computer anxiety refers to the degree of "an individual's apprehension, or even fear, when she/he is faced with the possibility of using computers" (Venkatesh, 2000, p. 349). Computer playfulness is the degree of cognitive spontaneity when interacting with the IS (Webster & Martocchio, 1992). Perceived enjoyment is the extent to which using an IS is perceived to be enjoyable by the users. Lastly, objective usability is the comparison of IS "based on the actual level (rather than perceptions) of effort required to completing specific tasks" (Venkatesh, 2000, pp. 350–351).



(Source: Venkatesh and Bala, 2008 pp. 280)

Figure 2.8 TAM3

As shown in Figure 2.8s, TAM3 also proposed several new moderating effects compared to TAM2. These new moderating relationships include perceived ease of use to perceived usefulness being moderated by experience, computer anxiety to perceived ease of use being moderated by experience, and perceived ease of use to behavioural intention being moderated by experience. The results from Venkatesh and Bala (2008) confirm TAM3's improvements over TAM2 in predicting a user's adoption and use of IS in an organization. Despite the improvements offered by TAM2 and TAM3, TAM still focused on just a single stage of adoption and use behaviour. There is no examination of post-adoption

decision of users' continuance intention, which is important for the long-term success of IS implementation.

In summary, although TAM2 and TAM3 were proposed, these models were not as well cited as the original TAM due to the fact that the model is viewed to be quite complex, and hence it is hard to apply TAM2 or TAM3 in studies that have different contextual settings. On the other hand, due to the original TAM's simplicity, it is a more parsimonious model and remain well adopted by IS researchers. Nevertheless, there are still some limitations of TAM and its subsequent models such as TAM2 and TAM3. For example, as claimed by Benbazat and Barki (2010), the abundance of papers that replicate TAM's original message has resulted an unwarranted belief that due to the same constructs and measures are being used, an accumulation of knowledge is occurring. IS scholars have over the years extended TAM to include variables such as trust, cognitive absorption, self-efficacy, personal innovativeness, job relevance, image, result demonstrability, disconfirmation, information satisfaction, top management commitment, cost, information quality, system quality, computer anxiety, personality, computer playfulness and many more. Despite making strong justifications to explain why each of these individual constructs are needed to add to TAM, these studies have basically provided explanations or antecedents for one set of belief perceptions (i.e., perceived usefulness and perceived ease of use) via another set of belief perceptions. There is also increasingly calls from the IS community to state that perhaps research based on TAM has reached its theoretical limits (Benbasat and Barki, 2007). This is because TAM has been applied so extensively that there is little

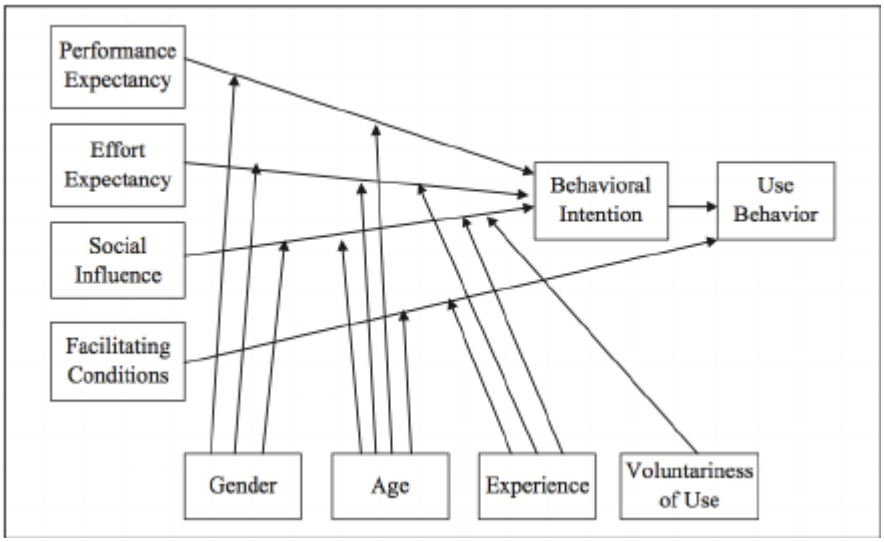
more to explore with TAM. There are even IS journals that state that they may not welcome research articles that simply just apply and extend TAM (i.e. Computers in Human Behaviour and Online Information Review). Therefore, in the field of IS, scholars have stated that newer theories are needed to help us further advance our knowledge of technology adoption and move beyond TAM studies.

2.3.2.4 Unified Theory of Acceptance and Use of Technology

The unified theory of acceptance and use of technology (UTAUT; Venkatesh et al., 2003) was developed approximately 14 years ago by Venkatesh et al. (2003), and it has been one of the most widely cited papers in information systems literature, with a reach that has extended beyond the information systems field itself. The original model was developed based on predictors derived from eight theories and was developed to explain employee acceptance and use of technology using four predictors—performance expectancy, effort expectancy, social influence, and facilitating conditions—and four moderators—gender, age, experience, and voluntariness. The UTAUT is based on the following eight models: the theory of reasoned action, the TAM, the motivational model, the theory of planned behaviour, a model combining the technology acceptance model and the theory of planned behaviour, the model of PC utilization, the innovation diffusion theory, and the social cognitive theory.

Performance expectancy is defined as the degree to which technology provides benefits to users when they perform certain activities. Effort expectancy is the

degree of ease associated with using technology. Social influence is the degree to which the user perceives how important that others believe he or she should use the technology. Lastly, facilitating conditions are the degree to which the user believes there is an organizational and technical infrastructure that supports the use of the technology (Venkatesh et al. 2003). According to UTAUT, behavioural intention to use technology is influenced by performance expectancy, effort expectancy, and social influence, whereas technology use is influenced by facilitating conditions and behavioural intention. Figure 2.9 provides an overview of the UTAUT model.



(Source: Venkatesh et al., 2003, pp. 447)

Figure 2.9 UTAUT

When revising the theory for consumer contexts, Venkatesh et al. (2012) also included hedonic motivation, habit, and price value as context-dependent predictors. UTAUT further theorizes that age, gender, experience and voluntariness moderate various relationships, whereas the revised UTAUT drops voluntariness for consumer settings. Although the theory was developed

for organizational contexts, scholars frequently apply the theory in non-organizational settings, and Venkatesh et al. (2012) subsequently modified it for consumer technologies by including hedonic motivation, habit, and price value as predictors.

Since its introduction, UTAUT has also been applied in a wide range of IT contexts, such as mobile banking (Zhou et al. 2010), e-government (Venkatesh et al. 2011), and electronic medical record (Hennington et al. 2007). Whereas some researchers applied this theory in different contexts without any modification, many others integrated it with other theories and extended it in their studies (Venkatesh et al. 2016). Although UTAUT has been applied extensively by IS scholars in the study of technology acceptance, there remain several important research extensions that can be conducted in UTAUT research. Venkatesh et al. (2016) in their review of UTAUT studies from 2003-2014, proposed that one extension to UTAUT studies can be based on "contribution of context-effect UTAUT". Such contribution use context distinguishing effects as explanations added to UTAUT. An example of this is the extension of UTAUT by Venkatesh et al. (2012) to UTAUT2, where they proposed and examined Mobile Internet acceptance, a consumer technology. As UTAUT was designed for work-based technology, UTAUT2 was proposed to examine variables that are specific to the context of Mobile Internet, namely hedonic motivation, price value and habit.

As Venkatesh and his colleagues (2016) note in their review of this theory, UTAUT still offers many promising opportunities for further theoretical

developments. First, they emphasize that more research is needed with respect to new UTAUT predictors. For instance, Eckhardt et al. (2009) enriched the social influence construct with five dimensions based on the source of the influence (i.e., customers, suppliers). Despite the various extension studies proposing the inclusion of numerous variables, it remains unclear which of these predictors should be included to increase the amount of explained variance in technology usage over and above the variance explained by current predictors. The choice of predictors becomes even more difficult since UTAUT studies frequently produce inconsistent results, with numerous studies reporting insignificant findings. For example, Teo et al. (2015) found that performance expectancy does not affect a user's intention to accept mobile payment, whereas effort expectancy is found to play a significant role. This contradicts with the findings from the original UTAUT which found performance expectancy and not effort expectancy to be the major determinant of the users' intention to use IS. Some of these inconsistencies could be attributed to researchers not applying the full UTAUT model or using sample sizes in their research that are too small (Teo et al. 2015). Consequently, it remains unclear how well the existing UTAUT variables predict technology acceptance and which new constructs add value to the theory.

Second, Venkatesh et al. (2016) also encourage further research on the influence of contextual factors on UTAUT, and they suggest shifting the focus from examining "UTAUT in context" to a focus on "UTAUT of context". Cross-context theorizing provides new insights on the generalizability of this theory and the context dependence of its predictors. These insights are needed since it

is unclear whether the importance of UTAUT predictors differ, for instance, across technologies, organizations, or countries. Although some studies have examined technology type (Wong et al. 2014) and location differences (Al-Gahtani et al. 2007), the literature still lacks a comprehensive assessment of these factors using a large cross-sectional data set, which is often only available in meta-studies. It therefore remains unclear which higher-level contextual factors exert moderating influences on UTAUT in addition to its individual-level moderators (e.g., age, gender). Venkatesh et al. (2016) explain that cross-context theorizing provides researchers insights to better interpret the empirical findings of their research and to modify UTAUT to better suit different contexts. Kamakura et al. (2014, p. 121) emphasize the importance of empirical generalization using meta-analysis by explaining that "grouping related studies (replications) can provide a more powerful test of specific theories than any single study as well as help identify boundary conditions for them."

In summary, when examining IS adoption studies that have implemented UTAUT, there are both formal and informal calls to suggest that UTAUT and perhaps by association the stream of research on technology adoption has reached its limit, with little or no new knowledge to be gained. However, it can also be argued that UTAUT has not actually been sufficiently and suitably replicated—an issue that is of great importance to IS scholars (Tsang & Kwan 1999), we could have one of two serious problems. Firstly, it is possible that a misspecification of UTAUT in the various applications and replications (albeit partial replications) led to the incorrect conclusion that UTAUT was robust. Secondly, although the extensions have included important variables, predictors

and moderators, absent the original specification, it is impossible to assess the true nature of the effects of the original and additional variables in order to arrive at a new UTAUT specification. Even if we considered there were good replications, applications, and extensions, various problems may plague us in drawing a clear way forward (Yong, 2012). Thirdly, most IS adoption studies propose new predictors for behavioural intention rather than use (Chong and Ooi, 2012). Studies have shown that many predictors suggested by other theories have the potential to be added to UTAUT because significant effects were observed in some extension studies. For instance, Eckhardt et al. l (2009) enriched the social influence construct with five dimensions based on the source of the influence (i.e., customers, suppliers). Despite the various extension studies proposing the inclusion of numerous variables, it remains unclear which of these predictors should be included to increase the amount of explained variance in technology usage over and above the variance explained by current predictors. The choice of predictors becomes even more difficult because UTAUT studies frequently produce inconsistent results, with numerous studies reporting insignificant findings. Thus, it remains unclear how well the existing UTAUT variables predict technology acceptance and which new constructs add value to the theory.

2.4. Summary of existing literature on HIT adoption studies

Based on the earlier theoretical discussions, this section aims to examine literature that have applied individual adoption theories in the context of HIT, to understand how these studies applied the respective theories as well as the gap in these studies. In order to identify empirical studies testing the technology acceptance of healthcare information technologies, the author searched through several databases, including ABI/INFORM, ProQuest, Science Direct, and Business Source Complete. Various keyword combinations such as "healthcare technology", "electronic medical record", "technology acceptance", "technology adoption" etc. were used in order to ensure all relevant papers are captured. A thorough search was further conducted using Google Scholar, Senior IS scholar's Basket of Eight journals (e.g. MIS Quarterly, Information Systems Research, Journal of Management Information Systems etc.), and major IS conference proceedings (e.g. ICIS, PACIS, ECIS) to identify additional articles in this research domain. Table 2.3 below provides a summary of selected past studies which examined the adoption of healthcare information technologies.

Table 2.3 Selected list of existing healthcare information systems adoption research

Authors	**Theory used**	**Types of IS studied**	**Summary of study**
Wu et al. (2007)	TAM	Mobile healthcare systems	This study used a revised TAM model to examine the determinants of mobile healthcare systems (MHS) acceptance by healthcare professionals. SEM analysis was used to test the model, and results showed that compatibility, perceived usefulness and perceived ease of use have significant effects on healthcare professional behavioral intent, whereas MHS self-efficacy had significant indirect effect on healthcare professional behavioral intent through the mediators of perceived usefulness and perceived ease of use. However, results did not validate the initial research hypotheses for technical support and training effects on the perceived usefulness and perceived ease of use.
Yi et al. (2006)	TAM/TPB/IDT (Innovation diffusion theory)	PDA	Integrating the TAM, TPB and IDT models, the authors of this paper developed a unified model and tested the resulting model in the PDA acceptance by healthcare professionals. Data was collected from 222 physicians in the US to test the model. Results showed good model fit, explaining 57% of physician's intention to accept an innovation.

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.
Zhang et al. (2010)	TAM2	Mobile homecare nursing	This paper focus on the adoption factors of mobile information technology among homecare nurses. A study was conducted using TAM2 on mobile homecare nursing that involved 91 Canadian nurses who used personal digital assistants for a month in their daily activities. Results show that nurse's perception of usefulness is the main factor in the adoption of mobile technology. Subjective norm and image within the organization are also significant antecedents.
Agarwal et al. (2017)	Ability-motivation framework/ Self-determination theory	Electronic Health Record	In this study, the authors draw upon an ability-motivation framework and self-determination theory to investigate the adoption of EHR at the level of the physician practice. Using data from 218 physician practices, their results suggest that while the ability components exhibit direct effects on adoption, the motivational components and their relationships to adoption are more complex. Although a practice may see the value in adopting an EHRS, this

			intrinsic motivator can be undermined by extrinsic pressures from external sources including regulatory agencies, pharmaceutical companies as well as peer practices.
Assadi and Hassanein (2014)	Self-determination Theory	Integrated Personal Health Record Systems	In this paper, the authors applied Self-Determination Theory (SDT) in order to have a better understanding of understanding of personal health record behaviour of individuals with different characteristics. The authors applied latent class analysis and found factors such as perceptions of usefulness and complexity of PHR systems to be important predictors of personal health record systems adoption.
Chen et al. (2008)	Expectation-confirmation Model	RFID	This paper examines RFID continuance intention in Taiwan hospitals setting. The study surveys caregivers and staffs in the emergency room department of five hospitals in Taiwan. The proposed model used ECM as a theoretical lens, and measures perceived usefulness by front end interoperability, backend interoperability and advantage over barcode. The model also examines whether the confirmation of users' expectations will lead to their satisfaction, which in turn will improve their continuance intention of using RFID.

Deng et al. (2014)	TPB/Value-attitude-behavior model/Aging characteristic factors	Mobile Health Service	This paper examines the adoption of mobile health services using data from older and middle-aged users. This paper explored a research model based on the value attitude behaviour model, TPB, and four aging characteristic constructs to investigate how older and middle-aged citizens adopted mobile health services. Their findings revealed that perceived value, attitude, perceived behaviour control, and resistance to change can influence middle aged users' decision to adopt mobile health services, while perceived value, attitude, perceived behaviour control, technology anxiety, and self-actualization influence behaviour intention of older user
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. 650 respondents from China participated in the study via survey. Their result revealed that perceived personalization and privacy concerns are positively and negatively associated with behaviour intention. Furthermore, trust also mediates the relationships between perceived personalization, privacy concerns and adoption intention.

Hsieh (2015)	TPB/Status Quo Bias theory	Cloud Computing	Hsieh (2015) in this study proposed and tested an integrated model to explain healthcare professionals' intention to use the health cloud service, as well as their intention to resist it. They collected data from 209 Taiwanese healthcare professionals. 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. On the other hand, attitude, subjective norm, and perceived behaviour control have direct positive influence on their intention to use cloud computing.
Kane (2007)	Social network theory	Information Systems	This study examines the role of IS proficiency and the ability of users to interact easily with an information system in the healthcare context. Data was collected from 557 members of 40 healthcare groups. The research examines three aspects of the group's user-system relationships, namely average IS use of the group, average IS proficiency of the group, and the centrality of the IS proficiency in the users' social network. In this research, only the centrality of IS proficiency is fully supported. By conducting additional qualitative data, they find evidence that the more central the IS proficiency is in a group, the better that group can work together to interact with the information systems.

Liang et al. (2014)	TPB	Hospital information system	This study explores the relationship between individual subjective factors of hospital medical staff and their hospital information system usage behaviour. The study develops a model uses the basis of the TPB model as its theoretical framework, adding in a new external variable, habit. The proposed model was tested on data collected from 278 employees in a hospital in China. Results from SEM analysis confirmed that individual subjective factors of medical staff play a significant role in behavioural intention to use hospital information system.
Mills and Chin (2007)	Self-efficacy theory	IT (in general)	This study examines the determinants of creative use of technologies by individuals. Creative use is defined by the authors to be the implementation of new and useful ways of applying organizational systems to solving business problems. This study draws on the self-efficacy theory to develop a theory-based conceptualization of creative use. Specifically, this research focused on the roles of domain-related computing knowledge and self-efficacy on creative use. 206 survey responses from clinical staff were analysed to test the model. The results of the analysis support the theorized model.
Moon and Chang (2014)	TRA/TAM/ISSM	Smartphones	The focus of this study is on the acceptance and use of smartphones in hospitals and the factors that influence users' attitude, social influence and intention of use. This study mainly adopted the TRA model as its theoretical framework, but modified it and incorporated the TAM and ISSM models. The model was

			tested against data gathered from a survey among 122 professionals in information development teams in Korean tertiary hospitals. Findings revealed the smartphone usage modes. Also, factors such as costs, contents quality, innovation, ease of use, and support demonstrated significant effects on user attitude. Portability, security, content quality, and innovation had significant effects on social influence. Finally, attitude and social influence were both significant to intention of use, thus validating the research model.
Ng and Kankanhalli (2009)	Job characteristics model/Relational job design model	Electronic medication administration systems (EMAS)	Authors of this paper draw upon job characteristics and relational job design theories to develop a model that investigates the individual impact of electronic medication administration systems (EMAS). To test the model, a survey was conducted among 112 nurses in a public hospital. The results of this study demonstrated the usefulness of organisational theories such as the job characteristics model and the relational job design model to understand the use of information systems and its individual impact.
Norten, A. (2012)	TPB	RFID	This study draws upon the ETPB model as introduced by Cammock et al. (modified version of TPB) to assess the following variables : privacy concerns; attitudes; subjective norms; controllability; and self-efficacy, and its effects on nurses' behavioural intention to use radiofrequency identification (RFID). Questionnaire responses from 106 nurses in the US were analysed using multiple linear regression method, and

			findings showed that all constructs together accounted for 60% of the variance in nurses' intention to use RFID technology. While most of the predictors of the model showed unique contribution or were held constant, privacy concerns, controllability, and self-efficacy did not show a significant contribution to nurses' behavioural intention to use the technology.
Venkatesh et al. (2011)	Social network	Electronic healthcare system	This longitudinal study uses social networks as its theoretical framework in investigating the nomological network in relation to e-healthcare system use. Data was collected following an e-healthcare system implementation from doctors, paraprofessionals, administrative personnel, patients, and usage logs. Results confirmed the research hypotheses.
Zhang et al. (2014)	modified TRA	m-health	In this study, the authors developed a modified theory of reasoned action (TRA) to examine m-health adoption intention. The modified model incorporated the nonlinearities between attitude and subjective norms as well as the moderating effect of gender. An empirical research was conducted among 481 respondents in China. Findings show that the research model with its nonlinearities enhances its explanatory ability and the modified TRA model can predict men's behaviour intention better than that of women. Further, it is found that facilitating conditions, attitude, and subjective norms are significant predictors of m-health adoption. Moreover, there are gender differences in m-health adoption.

Zheng et al. (2010)	Social Network	Electronic Health Record	This study investigated the influence of social interactions on physicians' adoption of an electronic health records (EHR) system using social network analysis. A social network survey was conducted to study the social interactions among 40 residents and 15 attending physicians in an ambulatory primary care practice. The survey assessed three types of interaction structures: professional network based on consultation on patient care-related matters; friendship network based on personal intimacy; and perceived influence network based on a person's perception of how other people have affected her intention to adopt the EHR system. Results indicate that social influence affecting physician adoption of EHR is predominantly conveyed through interactions with personal friends rather than interactions in professional settings.

For a full list of the summary of existing healthcare information systems adoption research, please see Appendix 1.

2.5 Assessment of existing studies on healthcare information technologies

Based on the review of existing studies, there are several observations that can be made. First, although TAM and UTAUT have both been examined in the context of healthcare related IS, many of the TAM studies are not able to provide much variance (Venkatesh et al., 2011; Chong et al., 2015). One of the reasons for this could be TAM's exclusion of factors that are specific and relevant to healthcare related information systems. UTAUT on the other hand, which is a much improved model for IS studies, has been examined in the context of

healthcare related technologies by Chong et al. (2015) and Kijsanayotin et al. (2009).

Second, although both TAM and UTAUT have been applied (Venkatesh et al., 2011), extended (Pai and Huang, 2011), and in some studies, integrated together (Trimmer et al., 2009) to examine various technologies in the healthcare settings, these studies do not apply the models accurately. For example, using TAM as a theoretical basis, Escobarrodríguez et al. (2012) studied the adoption intention of physicians and nurses on e-prescription and automated medication management system (EPAMMS). Their study found that perceived usefulness influences the adoption intention but does not directly affect the adoption intention of nurses and physicians. On the other hand, Ifinedo (2016) found that both perceived usefulness and perceived ease of use influence nurses' attitudes towards healthcare IS, which results in the behavioural intention to use IS. However, in both studies, there is no examination on whether perceived ease of use influences perceived usefulness which is what is proposed in the original TAM. However, just like most of the TAM related research, both studies extended TAM by including different variables such as perceived risks, perceived compatibility, training, computer knowledge and education. However, extending various variables to TAM reduces the parsimony of the original TAM, which is what makes TAM2 and TAM3 so difficult to apply to different contexts.

Third, UTAUT despite being a popular theory that are applied by scholars to study healthcare related technology adoption decisions, many results from these studies yield inconsistent result. In applying UTAUT to EHR, Kijsanayotin et

al. (2009) found that UTAUT variables such as performance expectancy, effort expectancy, social influence and experience can predict the intention to use EHR in healthcare community centres, and facilitating conditions and experiences can predict the actual use of EHR in community healthcare centres. Kim and his colleagues (2016), on the other hand, applied UTAUT to examine healthcare professionals' adoption of mobile electronic medical records in tertiary hospitals. Their study found that performance expectancy and effort expectancy influence healthcare professionals' attitude towards mobile Electronic Medical Record (EMR). Kim et al. (2016) also found that social influence and facilitating conditions both affect the intention to use mobile EMR. A further examination on these studies show that most scholars do not fully apply the UTAUT model correctly. For example, Diño et al. (2015) excluded facilitating conditions in their conceptual model without any justification.

Fourth, although TAM and UTAUT remain as the dominant theories in studying HIT adoption, there are other theories discussed which are being applied by other researchers such as IS Success Model and Risk Theory. These are presented in Table 2.4.

Table 2.4 Summary of other commonly applied theories.

Theories	Descriptions	Variables
IS Success Model	The IS success model proposed several variables of IS success including system quality, information quality, and user satisfaction (Delone and McLean 1992). Studies regularly measure relationship quality, loyalty, and fairness perceptions to describe user satisfaction with the IS.	Satisfaction Information quality Service quality Identification Relationship quality Loyalty Fairness
Risk theory	Risk theory proposes that IS acceptance depends on perceptions	General risk Security risk

	of issues related to technology usage risks, such as trust, security and privacy (Gefen et al. 2003; Pavlou 2003). Whereas some studies examine overall risk of technology use, others differentiate between various types of risk.	Privacy risk Trust
BIG 5 personality theory	The big 5 personality theory proposes that five personality variables are related to technology usage (Devaraj et al. 2008). The key personality traits are agreeableness, conscientiousness, extraversion, neuroticism, and openness to experience. More recent personality studies also examined the role of the user's altruism, impulsiveness, escapism, and optimism.	Agreeableness Conscientiousness Extraversion Neuroticism Openness to experience Altruism Escapism Impulsiveness Optimism
Socio-demographic	The IS literature provides inconsistent evidence for the impact of socio-demographic variables. Whereas some studies find an impact of variables such as income and social status on IS usage (e.g., Kwon and Zmud 1987), other studies treat them as moderators (e.g., Venkatesh, Thong, and Xu 2012).	Age Education Income Social status Tenure

Although researchers in the past have applied these theories, they are usually less dominant given that researcher would only select certain variables from these theories and use them to extend TAM or UTAUT (Chong et al., 2015). As such, prior studies that have employed variables from theories such as IS Success Model would not use them as the theoretical foundation in adoption studies, but instead will view them as an extension of TAM or UTAUT.

2.6 Gaps in existing technology adoption studies in the context of HIT and EHR

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

Although both TAM and UTAUT are both widely used to study healthcare technologies adoption decisions, given that UTAUT is developed based on a unifying eight existing IS adoption theories including TAM and Diffusion of Innovation theory, it is therefore appropriate to use UTAUT to form the theoretical basis of this research. UTAUT is extended to address some of the weaknesses identified and discussed in earlier sections as well as suggested by Venkatesh et al. (2016). These gaps present an opportunity for this study to further examine the reasons for healthcare professionals' willingness to adopt EHR. The gaps are discussed as follows.

Firstly, most of these studies have examined behavioural intentions and actual use of EHR. However, the adoption and use of these technologies alone does not mean a user will use the technology well. That is, these studies have neglected the user's performance in using the technology. To illustrate, imagine two users are using Microsoft Excel in their job location; one user can apply the appropriate formulas and use them correctly, and will thus perform better in using the technology rather than someone who uses Excel, but uses a calculator to perform the necessary calculations, and keys the results back to the Excel spreadsheet. Although performances have been examined in organization IT adoption studies (Melville et al., 2004), studies that examine the performance of users in using the technology remain sparse.

Secondly, despite UTAUT's popularity and impact as evidenced by the fact that it is one of the most highly cited recent IS acceptance model, many studies that claimed to have used UTAUT as a theoretical backdrop have never really implemented the full UTAUT model. And although UTAUT has been applied in research areas, studies on the acceptance of EHR in the healthcare industry are still very limited. This fact has seen a call by Kohli and Tan (2016) to IS researchers to contribute to further examine this line of literature in order to transform the healthcare industry.

Thirdly, existing studies have neglected the role of users' motivations when deciding to adopt a technology. That is, would a user who is more motivated perform better at adopting a technology? And if yes, what would influence their motivations? This study aims to address this by examining from the perspective

of consumer behaviour by psychologists and marketing researchers. Although Bagozzi et al. (1992) proposed a model that incorporated motivation to learn IT in technology acceptance, there has been little follow up research to understand what influences the motivation to learn IT. Lastly, in examining these acceptance studies, it was found that although many have examined individual characteristics, these studies have not examined how users in organizations need to collectively accept a new technology before it can be diffused successfully in an organization, making team learning behaviour an important concept that is proposed by this research.

Based on the discussions above, this study aims to extend UTAUT by incorporating Goal Attainment Theory and Work Team Learning to better understand what influences user behavioural intention to use and the actual use of EHR.

2.7 Pursuits of Goals

Researchers have in the past been interested in the goal pursuit behaviours (Hull, 1932, Louro et al., 2007, Bonezzi et al., 2011, Goes et al., 2016). Hull (1932) for example, found that rats will run faster when they are closer to food. Hull's study is one of the earliest papers that support the notion that distance to goals affect effort. Goal pursuits behaviours are also applicable to humans given that we are able to anticipate the results of goals, and apply efforts to achieve them (Goes et al., 2016). In most studies, researchers have focused on the presence and absence of goals, instead of the distance from the goals. For example, studies from Locke (1967, 1968) found that those who are given a set of goals would

achieve better performances. Other studies also found that by having more specific and difficult goals will have a strong effect when compared to “do your best goals” (Locke and Latham, 2002).

However, recent literature from Zhang and Huang (2010), Huang and Zhang (2011) and Goes et al. (2016) found that a person’s level of progress will also influence their motivation in the context of goal pursuit. For example, these studies examined how an individual’s level of progress may influence his or her motivation in goal pursuit. Despite these studies, there is sparse literature that examined how the rate of progress influenced their motivations. For example, when collecting stamps to obtain free coffee in a coffee shop, would information related to a customer’s rate of stamp collection influence his or her purchase decision? Similarly, when a person moves closer towards attaining his or her goal, would the person’s motivation increase (Huang and Zhang, 2011)? To address this gap, this research adopted concepts from Huang and Zhang (2011) and Goes et al. (2011)’s to examine how motivation on goal pursuits is influenced by the attainability and the velocity of achieving these goals, and in this context, the goal is the motivation to learn and accept EHR.

2.7.1 Goal Attainment and velocity of achieving the goals

Research in the past found that when an individual’s commitment to a goal is not certain or if it is low, focusing on the progress that is achieved will signal the individual’s commitment to the goal and motivate further pursuit (Koo and Fishbach, 2014, Huang and Zhang, 2011). While a key question for researchers

to answer in goal pursuit relates to what will determine a person's commitment to the goal, what information is more motivating in establishing goal commitment? To address this, Huang and Zhang (2011) stated that goal commitment represents an individual's decision to pursue a goal with the expectation of eventually achieving the goal. Therefore, committing to the goal will be based on the individual's perception that the goal is attainable. Zhang and Huang (2010) also stated that in the early stages of pursuing a goal, motivation is derived based on the belief that the goal is attainable; when an individual asks in the early stage of goal pursuit, whether he or she "can get there", that is motivation that is derived from goal attainment. Thus, as stated by Zhang and Huang (2010), in the early stage of goal pursuit, individuals are motivated by the question of "Can I get there?", and they will seek answers to confirm that the goals are attainable.

However, goal attainment will not dominate for long in the process of goal pursuit. When an individual has accumulated enough progress towards the goal, there will be a feeling of confidence that they are more likely to attain the goal, and therefore are more committed in the goal pursuit (Huang and Zhang, 2011; Wood and Bandura, 1989). At this stage, the question of "Can I get there?" will no longer dominate an individual's motivation. Instead, an individual will now be focusing on "when will he or she get there?". For example, in collecting stamps to redeem for a free cup of tea, an individual who has collected a sufficient number of stamps would no longer be concerned whether he or she will reach the goal of getting the free cup. Instead, the individual is more like to

focus on how much longer it would take for him or her to collect the sufficient number of stamps it would take to redeem for the award.

2.7.2 Goal pursuits in IS learning and adoption

Although studies on goal pursuits have focused in the area of consumer behaviour and conducted experiments in different contexts such as donation intention and product rewards (Huang and Zhang, 2011), there is very little application on the concept of goal pursuit in the context of IS adoption and use, in particular when a user is learning how to use an IS. The use of an IS also motivated by goal pursuits behaviour (Goes et al., 2016). When a user is learning to play a computer game for example, whether how long he or she will take to learn how to use the game, whether he or she thinks that he or she can win the game, or how soon he or she can win the game are all motivated by goal pursuit theory. More importantly, most existing IS adoption theories such as TAM/UTAUT have neglected the importance of "motivation to use the IS." Instead, most of these studies have focused on the intention of using IS.

In this thesis, it is proposed that the motivation to learn how to use the technology will be a more relevant predictor of actual use of the technology than the behavioural intention. Technology education is an important concept that was first proposed by Bagozzi et al. (1992)'s Theory of Trying. In developing their Theory of Trying, Bagozzi et al. (1992) seek to address an important gap in previous technology acceptance studies– the process in learning to use computers needs to be better examined and understand within the adoption

process. In existing literature that focuses on discrepancy reduction in self-regulation (e.g. Locke and Latham, 1990), the speed of progress in pursuing a goal signals how effective the process is as it will determine how long it will take to reach the end point (Huang and Zhang, 2011). Therefore, as suggested by Huang and Zhang (2011), instead of focusing on a static level of progress, the examination on velocity provides a progressive and dynamic feedback on one's efforts in the pursuit of goals (Huang and Zhang, 2011). One of the key motivations of this study is to apply the role of goal attainment and perceived velocity in affecting the motivation of an individual in learning to use the IS, and if he or she has better motivation in learning, it will result in the user being more likely to adopt the technology.

This thesis thus intends to examine whether perceived velocity (e.g. 'when will I get there') and perceived goal attainment (e.g. 'can I get there') will influence user motivation to learn EHR, and whether this will eventually lead to the adoption of EHR. And more importantly, as Huang and Zhang (2011) proposed, users will interpret their velocity differently in different goal attainment situations. For example, as users have different concerns at the early stage versus the later stage of goal pursuits, users may interpret the same information on velocity very differently to address these concerns. Therefore, the same velocity information may have different impacts on user motivation at different stages of the goal pursuit.

This research will therefore extend UTAUT, and combine factors related to how perceived velocity and perceived goal attainment of users' learning of EHR will influence their acceptance of EHR.

2.8 Team learning behaviour

In the study of technology adoption, most of the focus has been on an individual organization or individual adoption decision. But there is also an increase in IS literature that suggests that technology adoption at times may not be due to an individual adoption. For example, Lyytinen and Damsgaard (2001), in studying the adoption of inter-organizational inter-organizational information systems, proposed an adopter configuration analysis where the structure and strategy of an inter-organizational information systems are interdependent. For example, an inter-organizational information systems setup with a powerful customer as a hub and many suppliers as spokes frequently appears across diffusion studies. Thus there is a need where IS scholars should be looking beyond just the single organization that adopts inter-organizational information systems. Similarly, in examining inter-organizational system standards, Chong and Ooi (2008) found that it is important to examine the "co-adoption" decisions of organizations, rather than examining the individual organization's intention to adopt or use the technology. However, these studies have proposed to move beyond just a single organization's factors in adopting IS, but there are still limited studies that examine factors that may examine adoption of an IS from multiple users within an organization.

When looking at users within an organization, it is perhaps not surprising that often, when an organization introduces a new technology, it will involve the employees working as a team to accept the new technologies. For example, in applying an ERP system in an organization, employees from HR, Finance, Operations, as well as nurses and doctors will need to work together to use the system. If only an individual department is adopting the technology, or if there is an individual in the organization's unit that is willing to adopt the technology, then it is likely that the system will not be successfully diffuse in the organization.

Based on the discussions above, one key concept in examining group behaviour in the adoption of technology is the idea of team learning. As Edmondson et al. (2001) stated, when a technology requires a team for it to be in use, team learning will be necessarily involved for mastering the technical skills. Based on a qualitative field study on 16 hospitals, Edmondson et al. (2001) found that when implementing a new technology required substantial changes in the operating room's team work routine, the collective team learning process plays a crucial role in the implementation success. Brown et al. (2010) also examined whether familiarity with communication partners will influence the performance and effort expectancy of using collaboration technology.

Edmondson (1994) in proposing a Model of Team Learning, proposed that team learning behaviour can influence a team's learning performance. The concept of team learning behaviour is derived from the organizational learning literature. Based on the componential theory of creativity (Amabile, 1996), the factors that

foster individual learning will eventually influence individual creativity. This is further proposed by Hirst et al. (2009) that the dispositional differences in goal orientations will motivate an individual to either seek out or avoid the opportunities for learning and creativity, and in terms of the contextual influence provided by the team learning behavior. Model of Team Learning posits that team learning behaviour such as seeking feedback, discussing errors, seeking information and feedback from others are proposed to have an influence on the outcomes of team performance. These team learning behaviours are derived from studies related to management literature. For example, past literature found that a team can perform better than the individual managers seeking feedback from outside the team (Ancona and Caldwell, 1992). Further, research and development teams that work together to experiment frequently will also learn better. Schein (1993) also found that performance in team learning can also be enhanced where there is information related to the source of errors. Discussing these errors will enable team members to find out what did work as planned, and learn from these mistakes.

This research proposes that team learning behaviour can have an impact on the motivation and use of ERH by healthcare workers. The concept of learning and its influence on technology adoption is not an entirely new concept and has been examined in previous studies by Hsu et al. (2007) and Hartzel (2003). However, these studies have mainly focused on an individual's learning ability, which is measured by computer self-efficacy. Given that in organizations, team members in different departments or units work together to use the technology, this research argues that the ability for team members to learn increases when

members seek feedback and discuss errors and will result in better team learning and adoption of EHR. While it is not this thesis' aim to examine and propose an alternative to methodological individualism, previous studies (e.g. Sarker et al., 2011; Sarker and Sarker, 2009, Venkatesh et al., 2016) showed that it is important to consider group or team related factors in technology adoption studies when the context is appropriate.

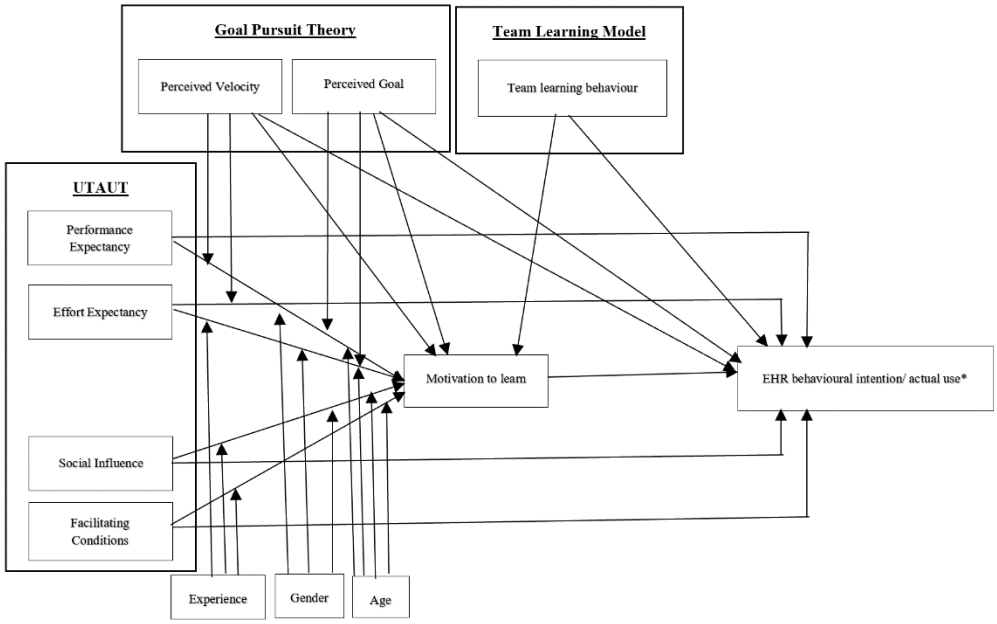
2.9 Summary of Chapter

This chapter presented an overview of EHR, as well as EHR in Malaysia. Technology adoption theories related to both organizational and individual technology adoption were discussed. Previous literature on HIT adoption were summarized and discussed. Based on the summary, this chapter also discussed the gaps in existing theories that have being applied to study HIT and EHR. A review of goal pursuits theories and team learning behaviour were also discussed. The next chapter presents the conceptual model and the development of hypotheses in this dissertation.

CHAPTER 3 CONCEPTUAL MODEL AND HYPOTHESES DEVELOPMENT

3.1 Introduction

Based on the previous sections on theoretical discussions, this study proposes the following conceptual model:



Note 1: The model will be tested 3 times based on data collected over a 6-month period in 3 intervals.
**Note 2: In T1, behavioural intention is the dependent variable of the study, while in T2 and T3, actual use is the dependent variable.*

Figure 3.1 Conceptual Model

This conceptual model's theoretical foundation is built upon the UTAUT. As compared to the original UTAUT model, this study differs in the following ways. Frist, goal pursuit theory (i.e. goal attainment and velocity of achieving the goal) and the team learning behaviour model are applied to extended UTAUT. Second, motivation to learn EHR is introduced to this model. This aims to

bridge the intention-behaviour gap (Sniehotta et al., 2005) whereby the intention to adopt a technology may not necessarily lead to sustained adoption. As such, the proposed model aims to bridge this gap by incorporating the motivation to learn EHR, and to test if it leads to the actual use of EHR instead of focusing just on intentions. Third, the model examines the three EHR adoption stages, namely in T1 pre-implementation stage (month 1), T2 implementation stage (month 2-3), and T3 sustained implementation stage (month 4-5). Therefore, unlike many existing UTAUT studies that applies cross sectional data, this study applies longitudinal data to examine the influence of predictors on EHR use at different stages of an implementation. Fourthly, in UTAUT, there is only direct effect from facilitating conditions to use behaviour, while the rest of the UTAUT predictors have direct relationship with behavioural intention that leads to use behaviour. In this study, the UTAUT predictors are proposed to have direct influence on both behavioural responses, i.e. intention and actual use. Lastly, individual users' characteristics such as age, gender and experience are kept in the model as Venkatesh et al. (2016) stated that these moderators are important contributions of UTAUT which are often left out by other technology adoption studies. However, voluntariness to use EHR is excluded from this model because in the context of this research, the use of EHR is not optional and all employees have to use the system.

3.2 Hypotheses Development

In the next few sections, hypotheses proposed for this study will be discussed. The hypotheses will be discussed under the theories discussed in the earlier chapter, namely UTAUT, goal pursuits theory, and team learning behaviour.

3.2.1 UTAUT Factors

3.2.1.1 Performance expectancy

Performance expectancy is defined as the "degree to which an individual believes using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, pp. 447). Performance expectancy is derived from variables in other theories such as perceived usefulness (TAM, TPB), extrinsic motivation (motivational model), job-fit (model of PC utilization), and relative advantage (innovation diffusion theory) (Venkatesh et al., 2003). Performance expectancy together with similar variables that are studied in different theories such as perceived usefulness in TAM, is one of the most commonly applied variables in technology adoption studies (Jeyaraj et al. 2006).

The relationships between performance expectancy and users' motivation to learn and adopt the technology has been studied extensively in different technologies ranging from ERP, EHR, RFID, Mobile Commerce (Chong et al., 2015; Chong et al., 2014). There are scholars such as Benbazat and Barki (2007) and Bagozzi (2007) who even stated that it is to almost certainty that a technology's performance expectancy (or perceived usefulness) will influence a user's motivation in using the technology. Other scholars have supported this

through conducting meta-analysis such as those by Taiwo and Downe (2013) and Khechine et al. (2016), which confirmed that performance expectancy is one of the strong predictors of users' behavioural intentions to use a technology. Despite these confirmations via meta-analysis, there are studies that found contradictory results in the role of performance expectancy in influencing decisions to adopt technology For example, in Chong et al. (2012)'s study on mobile commerce intentions by users in both China and Malaysia, it was found the performance expectancy do not play any role in influencing both Chinese and Malaysian mobile users. The argument given by Chong et al. (2012) was that mobile devices are not entirely a new technology to most users, and hence, they already have a level of understanding of what benefits mobile commerce can bring forth to them, and hence other predictors in their studies play a more prominent role in affecting users' adoption decisions. There are also researchers who posit that in different countries, performance expectancy by users could be quite different. Im et al. (2011) for example, stated that performance expectancy would be greater in countries that have lower power distance, as well as in a more individualistic culture. This, according to Im et al. (2011), means that the users in countries such as the United States are more likely to make independent decisions. When compared to countries such as Malaysia which has higher power distance and is a more collective culture performance expectance will still be an important consideration to users, but the impact of it may be less compared to countries such as the United States (Chong and Ooi, 2008). There are situations where performance is not the sole concern of users such as in studying e-government, mobile games and hedonic systems (Venkatesh et al., 2011; Chong et al., 2012)

Given the inconsistencies in previous studies, it would be useful to re-examine the role of performance expectancy in influencing the motivations of users to learn the technology, especially when the context of this study is different from past studies (i.e. EHR and in Malaysia).

In the context of EHR, it is likely that if healthcare professionals perceive EHR or other HIT to achieve more advantages when compared to previous technologies or processes (e.g. traditional paper-based system), then they would shift towards using the technology (Chong et al., 2015). Thus, performance expectancy should play an important role in predicting healthcare professionals' motivations to learn how to use EHR. However, it should be noted that in most of the UTAUT/TAM studies, performance expectancy is measured using cross sectional data, and it is often measured in terms of users' intentions to use the technology (e.g. prior to using the technology). In using a technology, there could be potential changes in performance expectancy when users have used the technology in the long run. As Chong et al. (2012) found in their studies, mobile commerce users are not influenced by performance expectancy when they are not new to the technology. Chong and Chan (2012) in studying RFID diffusion in healthcare organizations, found that performance expectancy (i.e. Relative Advantage) plays an important role in early diffusion decisions (i.e. evaluation), but not in the later stage of diffusion such as adoption and creating routines. Venkatesh et al. (2011), in proposing a two-stage IS continuance model that integrates UTAUT, stated that performance specific expectations of technologies are subject to change after user experience. Similarly, in the UTAUT, performance expectancy is only a predictor to users' behavioural

intentions, but not the actual use of the technology (Venkatesh et al., 2003). Based on these discussions, this study hypothesizes that:

H1a Performance Expectancy will have a significant and positive influence on behavioural intention to use EHR

H1b Performance Expectancy will have a significant and positive influence on motivation to learn how to use EHR, but the influence will decrease over time.

H1c Performance Expectancy will have a significant influence on actual use of EHR, but the influence will decrease over time.

3.2.1.2 Effort expectancy

Similar to performance expectancy, effort expectancy is one of the most studied variables in technology adoption research (Jeyaraj et al., 2006). Effort expectancy is defined as how "the degree of ease associated with using the system" (Venkatesh et al., 2003, pp. 450). Effort expectancy has been studied in related concepts such as perceived ease of use in TAM and complexity in innovation diffusion theory. Whether it is in work or for leisure related technologies, there is an abundance of studies that have examined the role of effort expectancy in predicting users' behavioural intention to use a new technology, especially when we also include studies that have applied TAM (Chong et al., 2012). Benbazat and Barki (2007) and Bagozzi (2007) have also stated that it is no longer a surprise to find the positive link between the effort expectancy (or ease of use) of a technology and the users' behavioural intention to use the technology. Thus it is not a surprise to find that in complex technology,

the adoption rate will be much lower (Brown and Venkatesh 2005). In self-service technologies that are easy to use, users are more likely to be satisfied and adopt the technology (Blut et al., 2016).

Nevertheless, it should be noted that in various well-cited articles published on UTAUT/TAM such as by Venkatesh et al. (2003), Al-Gahtani et al. (2007), Wei et al. (2009), and Chong et al. (2012), their findings found that there is no direct relationship between effort expectancy and users' adoption of technologies. There are arguments made in some organizational or work-related technologies, it is likely that employees are expected to use the technologies, hence expectations related to effort may not be the key concerns (Venkatesh et al., 2011). The inconsistency in terms of results suggest that different technologies or contextual factors may see a different influence of effort expectancy on users' motivation to learn to use a technology (Venkatesh et al., 2016; Chong et al., 2012).

The influence of effort expectancy on behavioural intention of the technology is also not expected to remain static over time. While effort expectancy will be an important determinant of technology learning and use, the perceptions should only be well-formed after having the experience of using the system (Venkatesh et al., 2011). After using a technology, a user's perceptions on the efforts it requires would be adjusted to reflect various aspects of experience (Chong and Chan, 2012). As stated by Venkatesh et al. (2011), effort expectancy is likely to hold true after the initial behavioural intentions. However, in the longer run, once users start to be familiarized with the system and know the user interface

well, effort expectancy should no longer remain an important influence where a user's concern would be determined by other expectations (Chan and Chong, 2013). Therefore, this study hypothesizes that:

H2a Effort Expectancy will have a significant and positive influence on behavioural intention to use EHR

H2b Effort Expectancy will have a significant and positive influence on motivation to learn how to use EHR, but the influence will decrease over time.

H2c Effort Expectancy will have a significant influence on the actual use of EHR, but the influence will decrease over time.

3.2.1.3 Social influence

Social influence is defined as "the degree to which an individual perceives that others believe he or she should use the new system." (Venkatesh et al., 2003). In other words, an individual's intention to use technology may be influenced by how he or she believes other individuals will view him or her after having used the technology. Social influence or subjective norm is derived from TRA, and it predicts general behavioural intentions in a voluntary context. However, different from subjective norms, social influence in UTAUT is system and application specific, while subjective norms relate to non-system specific behaviour (Al-Gahtani et al., 2007).

Previous studies have examined social influence as a variable in the adoption of other healthcare technologies, such as RFID (Chen et al. 2008), healthcare

robots (Alaiad and Zhou 2014) and telehealth (Diño and de Guzman 2015, Cimperman et al. 2016). While some studies have found that there is a significant relationship between the influence of the people in the individual's immediate environment, such as colleagues from the workplace, and the individual's behavioural intention (Wills et al. 2008, Ifinedo 2012), there were also studies that conflict with these results, finding no significance in the relationship between social influences in individual's behavioural intention to use healthcare technologies (Chau and Hu 2001, Schaper and Pervan 2007). Such contradictory results could be due to of the context of technologies studies (Chong, 2013) or cultural differences (Al-Gahtani et al., 2007; Venkatesh and Zhang, 2010). In Al-Gahtani's replication of the UTAUT model in studying computer use in Saudi Arabia, social influence is found to have stronger influence when compared to Venkatesh et al. (2003)'s study, which found social influence not to be a predictor of behavioural intention. The reason for this is due to the high power distance culture of users from Saudi Arabia. Furthermore, less individualistic countries such as Saudi Arabia or China will also value collective achievements and relationships (Chong et al., 2012), and hence social influence is an important predictor of behavioural intention and use of technology.

Most studies in the past, whether on healthcare or non-healthcare related technologies, have made the assumption that social influence's role on intentions and use behaviour should remain static over the course of users' interactions with the technology (Chong, 2013; Chong et al., 2015). But as stated by Venkatesh et al. (2011), when an individual is using the system, his or her

using the system could either confirm or reject prior expectations of the system, and this in turn may weaken the influence of others who created the expectations. Also, perceptions on social influence can be adjusted during the system user stage, as the user adjusts his or her pre-social influence perceptions as they observe others' performance of the behaviour, or the availability of new information, or the changes in colleagues', friends' and peers' opinions.

Therefore, we propose the following hypotheses:

H3a Social influence will have a significant and positive influence on behavioural intention to use EHR

H3b Social influence will have a significant and positive influence on motivation to learn how to use EHR

H3c Social influence will have a significant influence on actual use of EHR, but the influence should increase over time.

3.2.1.4 Facilitating conditions

Facilitating conditions are defined as the degree to which an individual believes that organizational and technical infrastructure exists to support the use of EHRs. It is often being regarded as a "belief related to one's control over the use of IS" (Venkatesh et al., 2011, pp. 534). In UTAUT, facilitating conditions are theorized to have a direct influence on user's behavioural intention and actual use of IS.

Facilitating conditions can come in the form of technical training, peer and/or leader guidance and assistance provided by the organization. In the case of Malaysia, EHR adoption in the healthcare sector is hampered by challenges related to system integration, and the lack of standard operating procedures, such as care pathways, clinical professional guidelines and operational policies, a prevalent obstacle towards successful system integration (Ghani, Bali et al. 2008). In addition, Malaysia is a developing country and digital literacy among healthcare staff in Malaysia is generally low (Ghani, Bali et al. 2008). Nurses therefore need to be equipped with the knowledge and resources to use EHR with the support of the organisation in which they work. Moreover, many studies with empirical evidence have shown that facilitating conditions have a significant effect on behavioural intention in the usage of technology (Kijsanayotin et al. 2009; Sharifian et al. 2014; Chong et al. 2015).

Similar to earlier discussions on social influence, facilitating conditions are often being examined as being static using cross-sectional data. However, users may adjust their attitudes towards facilitating conditions based on the situations they are in. For example, when the support provided is not good, resulting in poor facilitating conditions, a user may adjust his or her attitudes negatively in order to be consistent with the situation (Venkatesh et al., 2011). Similarly, a user will be more likely to form positive attitudes when there are adequate resources given. If a user encounters good facilitating conditions (e.g. better technical support in using the software and good online help) than expected in the early stage, to the result will be higher satisfaction, and this will lead to better post-usage, and this in turn will lead to continuance intention (Venkatesh et al.,

2011). Thus facilitating conditions should play an important role in the motivation to learn and use a system from an early stage to later stage IS use.

Thus, the following hypothesis is proposed:

H4a Facilitating conditions will have a significant and positive influence on behavioural intention to use EHR

H4b Facilitating conditions will have a significant and positive influence on motivation to learn how to use EHR

H4c Facilitating conditions will have a significant influence on actual use of EHR, but the effect should reduce over time.

3.2.2 Motivations and Goal Pursuits

3.2.2.1 Perceived Goal Attainment

Previous studies on the dynamics of self-regulation proposed that in a scenario when an individual's commitment to a goal is not certain, focusing on the progress achieved will signal his or her commitment to the goal, and will motivate further pursuit of the goal (Koo and Fishbach, 2014). But Huang and Zhang (2011) state that since goa140l commitment is an individual's definitive decision to pursue a goal with the expectation that he or she will eventually attain the goal, the commitment towards the goal should first be perceived as attainable by him or her. In this study, perceived goal attainment is the degree to which an individual believes that a goal is attainable or achievable. As stated in Bandura (2001)'s social-cognitive model, a person's willingness to pursue a goal will

increase as the belief that the goal can be attained as effort also increases. This is also supported by other theories such as value-expectancy model and goal-setting theory, which both support the notion that cognitive assessment of a person's chance of reaching the goal will influence the person's decision to adopt the goal (Huang and Zhang, 2011). Thus, the motivational effect of goals will not be present if the goal is too challenging (Goes et al., 2016). Therefore, a person's commitment to pursue a goal (e.g. learning to use EHR) will very much depend on whether the individual believes the goal is attainable (Zhang and Huang, 2010). In the context of technology adoption and use, as most of the healthcare professionals (i.e. nurses and doctors) are used to the manual paper process of keeping heath records, they will need to feel that the goals of learning and using EHR should be attainable before actual adoption and use.

Despite the importance of goal attainment, once users' are closer to reaching his or her goals, the effect of goal attainment of user motivation should reduce. This is especially true when the goals appear to be more and more within the user's reach (Goes et al., 2016). Perceived goal attainment then should have a gradual reducing effect in the motivating users after some time where users feel that the goal is now attainable. Prior studies also suggest that upon goal attainment, goal efforts may drop. This is supported by Dewey (2007) and Goes et al. (2016), where the Drive-Reduction Theory suggests that once the satisfaction from reaching a goal stops, this will lead to a drop in effort. Thus, it should be expected that user efforts will drop as soon as a goal is reached (Goes et al., 2016). Accordingly, the following hypotheses are proposed:

H5a Perceived goal attainment will have a significant and positive influence on behavioural intention to use EHR

H5b Perceived goal attainment will have a significant and positive influence on motivation to learn how to use EHR, but the influence will reduce over time.

H5c Perceived goal attainment will not have a significant influence on actual use of EHR

3.2.2.2 Perceived Velocity

In the study of goal pursuits, the study on the progress level of attaining the goal (i.e. velocity of reaching the goal) has received significant attention in the field of marketing and social psychology (e.g. Zhang and Huang, 2010; Goes et al., 2016). According to Elicker et al. (2010), velocity is the rate at which people are approaching their performance target or alternatively the rate at which discrepancies are being reduced. The term discrepancies was referred to as the performance-goal discrepancies (Elicker et al., 2010). This study will draw upon a similar definition, whereby we define perceived velocity to be the perceived speed or rate at which an individual achieves his or her goal. Once this goal-attainment effect reduces (i.e. 'can I get there?'), a consumer or user will shift his or her focus. This is because through accumulating sufficient progress towards the goal, an individual will now feel more confident that the goal is achievable, and hence are they are more committed in the pursuits.

Once the attainment of goal is perceived to be certain, its effects on behavioural intentions and actual use of EHR may reduce, while users may pay more

attention to whether they are able to reduce the remaining discrepancy at an acceptable speed. At this stage, the focus on "when will I get there?" may increase its effect on behavioural intention and actual use of EHR. An example of this can be seen in a loyalty programme where a customer may be asked to collect 20 stamps to be redeemed for a reward. Initially the consideration for the customer may be whether such a goal is attainable. Once he or she has progressed to a certain stage, if the goal is now deemed as attainable, the customer will focus on how much longer he or she will need to collect the additional stamps for the reward (Zhang and Huang, 2010). The rate of progress will provide cues on the effectiveness of pursuing the goal because it will determine how long it will take to reach the end point. As stated by Huang and Zhang (2011), in a situation where the pursuit of the goal is not effective even as a person gains more experience, he or she will be motivated to correct their behaviour in order to ensure that the goal can be successfully achieved within the desired time frame (Brunstien and Gollwitzer, 1997, Huang and Zhang, 2011). As such, although both effects of perceived goal attainment are perceived velocity are important to behavioural intention and actual use of EHR, the role of "can I get there?" may be less than "when will I get there?" in the later stage of EHR adoption when the goal of learning to use the system is more attainable. Users will use velocity information to interpret how effective they are in reducing the remaining discrepancy and will then adjust their behaviour accordingly.

Thus, when achieving a goal, when a user is progressing quickly, he or she could be more motivated to finish the task as soon as possible or as best as one could

to close the remaining discrepancy. Therefore this study will investigate whether users in learning and adopting EHR, whether perceived velocity will influence their motivations of goal pursuit (i.e. learning EHR). Therefore, the following hypotheses are proposed:

H6a Perceived velocity will have a significant and positive influence on behavioural intention to use EHR

H6b Perceived velocity will have a significant and positive influence on motivation to learn how to use EHR, and the influence will gradually increase over time

H6c Perceived velocity will have a significant and positive influence on actual use of EHR

3.2.3 Team Learning Behaviour

Previous studies on individual adoption behaviours have examined the role of team related factors in determining the eventual success or failure in technology adoption. For example, team processes and outcomes supported by technology such as trusts in teams were examined by Sarker et al. (2011), agility in teams (Sarker and Sarker, 2009), group polarization (e.g. Sia et al., 2002) and group system interface (e.g. Sia, Tan, Wei, 1997). These studies use team related factors and incorporate them into the technology acceptance related models' baseline to examine how team-level factors influence individual acceptance and use of technology. Such studies are supported by Venkatesh et al. (2016) who believe that the approach is able to address weaknesses of some individual-level

studies, which may have delineated the impact of organizational factors on technology adoption.

Sarker and Valacich (2010) proposed that studies on group within the IS discipline have largely being based on the paradigm of methodological individualism, which may lead of potentially incorrect conclusion in these studies.

The importance of learning behaviour in affecting innovation adoption is studied at various levels ranging from organizations, teams and individuals (Venkatesh et al., 2016). Edmondson (2003) in studying the implementation of new innovations (i.e. new technology for cardiac surgery) in hospitals, found that team learning process will influence the implementation success of the technology. Edmondson (1999; 2003) and Edmondson et al. (2001) studies found that team learning plays an important role in new technology implementations in hospitals. One of the key arguments in these studies is that because new technologies disrupt organizational routines, people therefore need to communicate and coordinate to create new routines, and therefore participate in collective learning process (Edmondson et al., 2001). This is true in the context of EHR implementation as it affects healthcare workers' previous routines. Doctors, for example, will need to record patient diagnosis in a computerized system. Nurses will need to work with EHR in dispensing medicines and keeping the medical records up to date. Administrators in hospitals will no longer keep manual records of patient data, and instead will need to use EHR system to store patients' health records. To overcome such

disruptions to previous routines, team learning behaviour whereby members seek feedback, discuss possible errors, obtain information and feedback from others are likely to motivate each other to learn about new technology as well as successfully adopting it (Edmonson, 1999). The following hypotheses are therefore proposed:

H7a Team learning behaviour will have a positive and significant influence on behavioural intention to use EHR

H7b Team learning behaviour will have a positive and significant influence on motivation to learn how to use EHR

H7c Team learning behaviour will have a positive and significant influence on the actual use of EHR

3.2.4 Motivations to learn EHR and behavioural intention and actual use of EHR

Previous literature on IS adoption have found the roles of motivations have an influence on the use of new technologies. For example, in UTAUT, Venkatesh et al. (2012) extended UTAUT2 by including hedonic motivations when examining the acceptance of consumer IS. There are other scholars who further applied extrinsic and intrinsic motivations to technology acceptance models such as TAM or UTAUT (Zhou, 2011; Chong, 2013; Venkatesh et al. 2012; Lacka and Chong, 2016; Lee et al., 2005; Teo et al., 1999). In these studies, motivations include factors related to rewards, punishments, enjoyment, and improvements in using an IS. However, Yi and Hwang (2003) stated that users with a 'learning goal orientation' approach a task with the intention to

understand something new or to enhance their level of competence. These individuals believe that learning ability is an incremental skill, and thus one can continually improve by acquiring knowledge and perfecting competency (Mun and Hwang, 2003). Similarly, users who are motivated to learn a new system (i.e. EHR), will believe that they can improve by learning the system better, and continuously improve their competency, and hence will be more willing to adopt and use the system. In this case, this study has extended UTAUT as well as technology adoption studies by proposing the link between the motivation to learn the system and the eventual acceptance of the system.

H8a Motivations to Learn EHR will have a significant and positive influence on behavioural intention to use EHR

H8b Motivations to Learn EHR will have a significant and positive influence on the actual use of EHR

3.2.5 Moderating Effects

3.2.5.1 UTAUT moderators

One of the key contributions of UTAUT is that it proposed the moderating relationships between the predictors proposed (i.e. effort expectancy, performance expectancy, social influence and facilitating conditions) and experience, gender, age and voluntariness of use (Venkatesh et al., 2003). As Venkatesh et al. (2017) stated, the majority of UTAUT did not employ the full UTAUT model, and this is mainly by excluding the moderators, intentionally or not. In order to examine the extended UTAUT on EHR, the moderators are also

included in this study. However, in the context of this research, the use of EHR is mandatory among healthcare employees as implemented by the healthcare company. Therefore, only age, gender and experience are included, while voluntariness is not included as a moderator in this study's research model.

Gender

UTAUT proposed that gender has a moderating influence on performance expectancy, effort expectancy and social influence. Gender is theorised to have a moderating effect due to the stereotypes and perceived differences that are associated with genders in using technologies (Venkatesh and Morris, 2000). Such stereotypes may include differences in beliefs and competency in males versus females. Tan and Ooi (2018) also stated that gender differences in the use of technology can be explained by the socialization process, where the different decision-making among men and women could be attributed to society dictates on how they should behave. Likewise, Deng et al. (2010) stated that based upon social role theory, females may be characterized by emotional traits, while males are more likely to be influenced by instrumental traits.

Previous studies on healthcare technology adoption have tended to find no moderating role on the relationship of the constructs to behavioural intention of healthcare technology (Whetstone and Goldsmith 2009, Venkatesh, Sykes et al. 2011, Diño and de Guzman 2015). However, their results are not consistent as some empirical evidence has also found the moderating effects of gender on technology adoptions, although not in the context of healthcare technology

(Gagnon et al., 2014). These inconsistent results could be due to the moderating effects of gender variance across different technological contexts. For example, Diño and de Guzman (2015)'s study found that gender has no moderating effect because of the established notion that technology systems are becoming more accessible to both genders, regardless of technology capacity and social background.

However, in the case of Malaysia, the gender gap remains salient as indicated in Malaysia's extremely low ranking in the Global Gender Gap Index, supported by statistical data on male-female gaps in education, economic mobility and participation in political roles (Hirschman 2016), and hence there could be potential differences in behaviour exhibited by males and females in using new technology. Based on the above discussion, this study hypothesizes that the gender divide in Malaysia reinforces gender roles and stereotypes, therefore having a moderating effect in the relationship between performance expectancy, effort expectancy and social influence on behavioural intention to use EHRs.

Hence, this study proposes the following hypotheses:

H9a The effect of performance expectancy on motivation to learn to use EHRs will be moderated by gender.

H9b The effect of effort expectancy on motivation to learn to use EHRs will be moderated by gender.

H9c The effect of social influence on motivation to learn to use EHRs will be moderated by gender.

Age

UTAUT model proposed that age of a user will moderate all the UTAUT predictors (Venkatesh, Morris et al. 2003). The moderating role of age has also been validated in previous studies on the adoption of healthcare technology (Phichitchaisopa and Naenna 2013).

The theoretical justification behind this moderator centres around the considerations that older people tend to find it difficult to adapt to change and are more likely to rely on the opinion of others (Venkatesh, Sykes et al. 2011). These considerations will apply well in the context of this study as the EHR system is a relatively new technology in Malaysia and some older employees were likely hired and medically trained before the introduction of the EHR system. On the other hand, the younger employees who were more likely to have been exposed to different technologies at an earlier stage of their lives and are therefore more adept at using them would likely have stronger intention to use the EHR system. For example, Chong et al. (2012) in studying Malaysian consumers' adoption of mobile commerce, found that younger users are more likely to adopt the technology when compared to older users. As stated by Wong et al. (2012), younger and older users tend to use technologies with different needs, interests and goal orientations. Therefore, this study proposes the following hypotheses in accordance to the original UTAUT theoretical model:

H10a The effect of performance expectancy on motivation to learn to use EHRs will be moderated by age.

H10b The effect of effort expectancy on motivation to learn to use EHRs will be moderated by age.

H10c The effect of social influence on motivation to learn to use EHRs will be moderated by age.

H10d The effect of facilitating conditions on motivation to learn to use EHRs will be moderated by age.

Experience

In the context of this study, experience is defined as the past use of health information technology. Although previous studies may have measured experience such as their experience in using the devices (Chong et al., 2012), in the context of this study, experience measures their experience in using the previous system. The conceptual UTAUT model theorizes that experience moderates the relationship between effort expectancy to behavioural intention, the relationship between social influence to behavioural intention, as well as the relationship between facilitating conditions to use behaviour. The theoretical mechanisms behind experience as a moderator is the consideration that increased experience in using a technology may lead to a decline in problems that existed in the early stages of technology usage, which will in turn influence the effects leading to behavioural intentions over time (Venkatesh, Sykes et al. 2011). Several studies have also tested and confirmed the role of experience as a moderator (Thompson et al. 1994; Kijsanayotin et al. 2009), further validating its theoretical basis.

It should be noted that when the original UTAUT model was tested, the experience construct used aggregating data from three consecutive time periods over the course of six months (Venkatesh et al., 2003). However, this study operationalizes experience as the length of time that each respondent reported to have used e-Mediviron 1, the old EHR system. Thus, we propose that the experience of using e-Mediviron 1 will moderate the effects of effort expectancy, social influence and facilitating conditions. Thus, based on the discussion above, we propose the following hypotheses:

H11a. The effect of effort expectancy on motivation to learn to use EHRs will be moderated by experience.
H11b. The effect of social influence on motivation to learn to use EHRs will be moderated by experience.
H11c. The effect of facilitating conditions on motivation to learn to use EHRs will be moderated by experience.

3.2.5.2 Moderating effects by perceived goal attainment and perceived velocity

Perceived attainability in this study is operationalised based on the individual's belief that he or she will find it easy or difficult to achieve a given goal. This belief can stem from both perceived internal (such as perceived ability and skills) and external resources (such as perceived facilitating conditions). In addition, we propose that perceived attainability will have a moderating effect on performance expectancy and effort expectancy. Individuals who have a stronger belief that they will succeed in the task of using the EHR system may find it

more likely for them to enhance their job performance after successfully learning how to use the system. Likewise, those who are more confident that they will successfully achieve their task of learning to use the system may likely perceive that the system is not difficult to use.

Several studies on velocity highlighted the importance of velocity in self-regulation, in that velocity plays a role in producing satisfaction (Carver and Scheier 1990), and can predict mental focus and have an impact on one's ability to sustain interest and motivation (Elicker et al. 2010). Slowdowns' in velocity and low speed of discrepancy reduction were also argued to be a threat to an individual's commitment to goal attainment (Gollwitzer and B. Rohloff 1999). Interestingly, Gollwitzer and Rohloff (1999) posit that in situations where velocity is low, effort and performance increases because people spontaneously strive to keep to the desired velocity, leading to an increase in effort and performance.

In line with these claims, this study theorizes that perceived velocity will have a moderating effect on performance expectancy and effort expectancy. We propose that individuals who believe that they can achieve their goal of using the EHR system well at a high or desired speed will find it more possible that their job performance will improve by using the technology. Furthermore, we propose that individuals who perceive that they will attain their goal of using the EHR system well with high or desired velocity will find that the system is likely easy to use, and thus less effort is needed to use it.

H12a The effect of effort expectancy on motivation to learn to use EHR will be moderated by perceived attainment

H12b The effect of performance expectancy on motivation to learn to use EHR will be moderated by perceived attainment

H13a The effect of effort expectancy on motivation to learn to use EHR will be moderated by perceived velocity

H13b The effect of performance expectancy on motivation to learn to use EHR will be moderated by perceived velocity

3.2.6 Mediating effects of motivation to learn EHR

In the original UTAUT, it is argued that performance expectancy, effort expectancy, social influence and facilitating conditions are direct determinant of behavioural intention, and behavioural intention mediates actual use decision (Venkatesh, et al., 2003). However, there are also studies which suggest that users who have positive perceptions on the effort expectancy, performance expectancy, social influence and facilitating conditions of using a new technology are more likely to be motivated to learn the technology (Maldonado et al., 2009). Prior research also found that highly motivated learners will be more likely to use a new technology (Tan, 2013). Thus, it is expected that motivation to learn EHR would mediate the relationship between the UTAUT predictors and the behavioural intention and actual use of EHR. Therefore, this study hypothesizes that:

H14a: Motivation to learn EHR mediates the relationships between the UTAUT variables and behavioural intention to use EHR.

H14b: Motivation to learn EHR mediates the relationships between the UTAUT variables and actual use of EHR.

3.6 Summary of Chapter

In this chapter, a conceptual model based on UTAUT, perceived goal attainment, perceived velocity and team learning behaviour is proposed. This provided an overview of the conceptual model, as well as how the model will be examined based on longitudinal data. Data from what this research termed as pre-implementation (T1), implementation (T2) and sustained implementation (T3) will be collected for this research. This is followed by a discussion on the hypotheses proposed. The proposed hypotheses were based on factors related to UTAUT, goal pursuit theories and team learning behaviour. Relevant moderators and mediators were also hypothesized in this chapter. The next chapter will present the research methodology employed in this study.

CHAPTER 4 RESEARCH METHODOLOGY

4.1 Introduction

In order to examine the proposed conceptual model and hypotheses, this research adopts a questionnaire survey approach. The research design and research strategies employed in this research is first discussed in this chapter. The data analysis technique is then presented, with reasons provided to explain why PLS-SEM is chosen as the main technique employed in this research. The measurements used in this research is then discussed. Lastly, the data collection plan, sampling results as well as demographic or respondents in this research are also presented.

4.2 Research Design

The key role of research design is to connect the research questions to the data collected. The research design sits between the design of research and the data, showing how the research questions will be connected to data, and the tools and procedures that are applied in answering them (Zhang et al., 2000; Chong, 2009). The design of a research project should follow from the questions and fit them with the data. As cited in Chong (2009) and Zhang et al. (2000), the design is the basic plan for conducting empirical studies, and this includes main ideas such as strategy, sampling, and the tools and procedures that are used for collecting and analysing empirical data (Punch, 2000; Chong, 2009).

4.3 Research Strategies

There are two main approaches to collecting data for empirical studies- quantitative and qualitative methods. A qualitative research method allows for the study of selected issues in very specific detail. Nevertheless, by employing a quantitative approach, we allow the use of standardized instruments so that the different perspectives and experiences of people can fit a limited number of predetermined response categories, to which numbers are assigned (Chong, 2009). One of the key advantages offered by a quantitative approach is the ability for the research to apply the measurement of people to a limited set of questions, and this facilitates the comparisons and the statistical aggregation of the data. As a result, a broad and generalized set of result findings can be presented succinctly and parsimoniously (Patton, 1990).

Based on the earlier review of various technology acceptance theories as well as goal pursuits and team learning behaviours, a conceptual model to examine EHR adoption was developed. In order to answer the research questions as well as hypotheses proposed in this research, there is a need for this research to verify the theories proposed. The theory verification process is aimed to examine theories proposed more accurately, as well as to test the hypotheses that were derived from these theories (Punch, 2000). In management related studies, especially in the field of information systems, it is a standard practice to apply quantitative research to test theories. In a quantitative information system research, the study will usually start with a theory (or theories), deduce hypotheses based on the theory (or theories), and finally test these hypotheses to

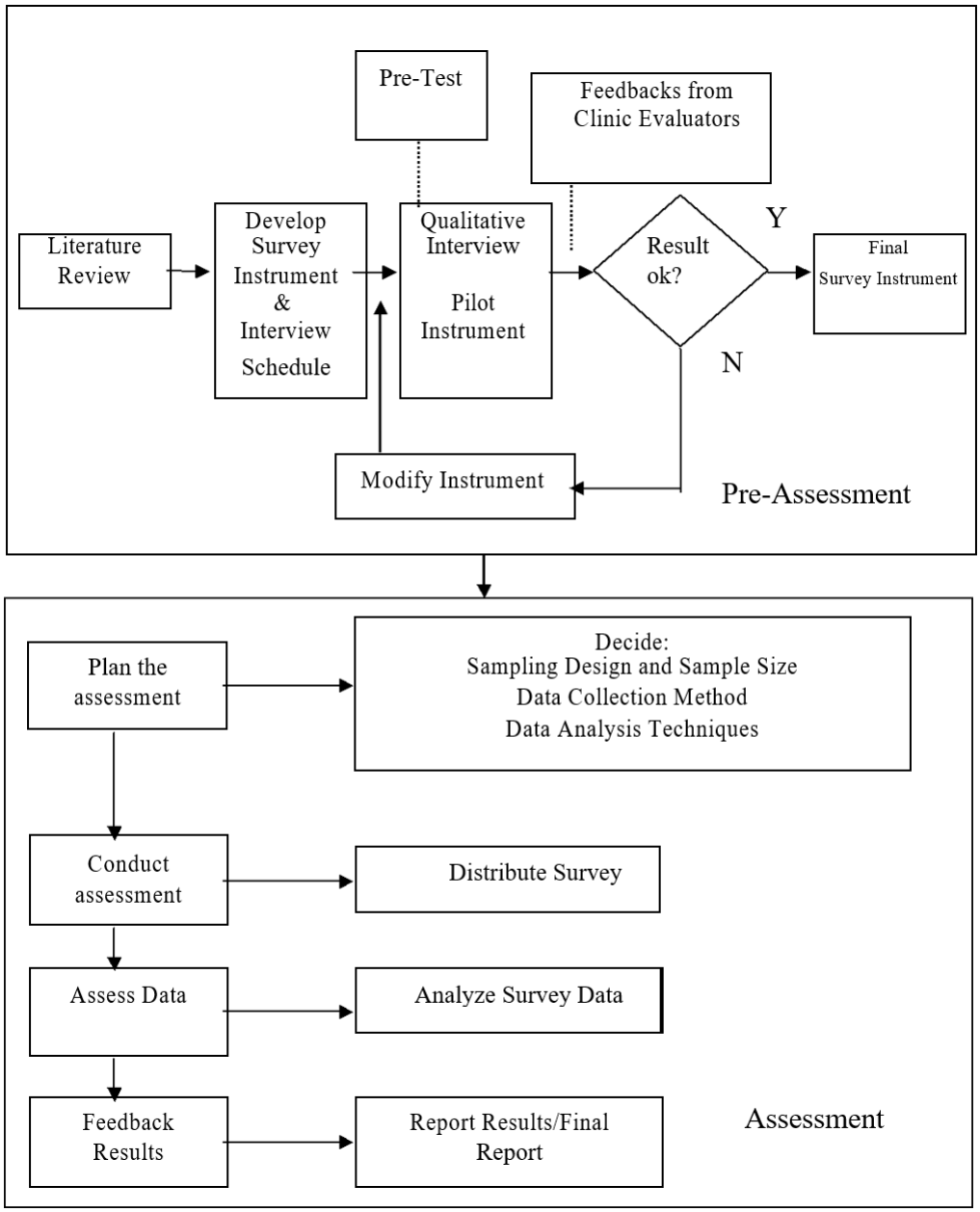
determine if they should be accepted or rejected (Zhang et al., 2000). Based on the process described, one of the most common way to collect and examine the data will be through a questionnaire survey (Patton, 1990). Questionnaire survey is also a method that has one of the lowest transaction costs involved. This is especially true when most surveys can be distributed and collected via the Internet (e.g. either via web portal or just sending through emails).

For this research, the key aims include examining the relationships between the adoption factors (i.e. UTAUT, goal attainment, perceived velocity and team learning behaviour) with the motivation to learn and adopt (i.e. behavioural intention and use) of EHR, a quantitative approach through the use of questionnaire survey will be deemed to be an appropriate method for this research. This is supported by Chong and Ooi (2008) which stated that as there are strong theoretical basis for identifying the variables in this research, as well as the proposed relationships, employing a causal design study using questionnaire is highly suitable.

This research employs the methodological processes employed by Chew (2007) and Chong (2009). This is summarized in Figure 4.1. There are two phases employed in this research and they include the first phase where a pre-assessment through a pilot study is conducted. In the second phase, measurement assessment, data analysis and findings will be discussed.

In the first phase, an initial questionnaire was developed in English, and was then translated into Malay in order to make it bilingual. A back-to-back translation process is employed by translating the Malay questionnaire to English, and compared with the original English questionnaire to ensure that meanings were not lost during the translation process. In order to conduct the pilot study, the survey was sent to 10 Malaysian clinics (i.e. Mediviron clinics) where 30 healthcare workers (i.e. doctors, nurses and administrators) anssered the questionnaires and provide feedback on where they believe the questionnaire could be improved. A qualitative research method where structured interviews were also conducted with several clinic managers to further obtain feedback on the questionnaire. The interviews were conducted face to face at various Mediviron Clinic branches. This process helped the researcher to refine the variables in the questionnaires, especially when certain questions were not clear to the managers. There were also recommendations from the participants in the pilot study to improve several questions. Once the pilot study was conducted, the second phase included processes such as planning and assessment; conducting the assessment to collect data and information; assessing the data collected; and providing recommendations based on the results (Chong, 2009). The overall research study plan is shown in Figure 4.1.

Figure 4.1 Research Study Plan (Adapted from Chong, 2009, pp. 165)



4.4 Data Analysis Technique

The research questions and hypotheses developed in this research involved testing the proposed conceptual model. In order to test the conceptual model, a survey questionnaire was designed and distributed to healthcare professionals in Malaysian clinics and hospitals.

Similar to previous technology adoption studies (e.g. Venkatesh et al., 2003; Venkatesh et al., 2012) as well as technology adoption studies in the context of healthcare (e.g. Chong and Chan, 2012), structural equation modelling (SEM) method is employed to this research. There are two main approaches for researchers to employ SEM, which are partial least square-SEM (PLS-SEM) or covariance-based SEM (CB-SEM). Table 4.1 below provides a rule of thumb summary on which SEM methods should be employed (Hair et al., 2017)

Table 4.1 - Rules of Thumb for Choosing SEM Method (Hair et al., 2017, pp. 444)	
PLS-SEM	CB-SEM
1. The research objective is exploratory.	1. The research objective is to confirm the structural and measurement theory.
2. The objective of the analysis predicting an outcome.	2. The measurement philosophy is estimation with the common factor model using only common variance
3. The key measurement philosophy is estimation with the composite factor model using total variance.	3. The research needs a global goodness of fit criterion.
5. The aim of the research is to explain the relationships between exogenous and endogenous constructs. 6.	4. The error terms require additional specification, such as covariation.
5. The structural and/or measurement models are complex (many constructs = 6+ and many indicators = 50+)	5. The structural model specifies non-recursive relationships.
6. The model use formatively measured constructs.	6. The structural and/or measurement models are much simpler (5 or fewer constructs and 50 or fewer indicators).
7. The sample size is small (N < 100).	
8. When data is not normally distributed.	

9. The scaling of responses is ordinal or nominal.	
10. The data is secondary/archival, particularly single item measures.	
11. The analysis involves a continuous moderator.	

Based on Table 4.1, most of the reasons associated for employing PLS-SEM are particularly relevant to this study. The reason for this is that the UTAUT model employed in this study is extended using new theories related to goal pursuits and team learning behaviour, while this study also include motivation as an antecedent to the adoption of EHR. Furthermore, the objective of this research is to predict what influence motivations and decisions of healthcare workers are in adopting EHR. The model presented in this study is also complex with many constructs and indicators. While the sample size of this study is not small, Hair et al. (2017) stated that it is also acceptable for data with a slightly larger sample size to employ PLS-SEM. This is demonstrated in the development of UTAUT2, where the sample size used by Venkatesh and colleagues were more than 1500 respondents. Furthermore, exogenous (i.e. UTAUT variables, perceived velocity goal attainment) and endogenous relationships (i.e. motivation to learn) will be examined in this research, whereby the conceptual model has more than 6 constructs, as well as more than 50 indicators. There are also single items used in this research such as age, experience and gender of the respondents. Lastly, there are several continuous moderators used in this study as perceived velocity and goal attainment.

4.5 Variables used in this study

4.5.1 UTAUT variables

The UTAUT variables (i.e. performance expectancy, effort expectancy, facilitating conditions and social influence) are all derived from Venkatesh et al. (2003). Similar to Venkatesh et al. (2003), 15 items (questions) were used to capture the four UTAUT variables. All the items used a 7 point Likert Scale, where 1 = strongly disagree and 7 = strongly agree. Despite arguments by scholars whether the Likert scale is interval or ordinal (Newman, 1994), consistent with Venkatesh et al. (2003) as well as most technology acceptance studies, this research used Likert scale as interval scales. The reason for this is due to the fact that Likert scales are very commonly used with interval procedures provided the scale item has at least seven categories, which is what has been applied in this study (Jaccard and Wan, 1996). Furthermore, given that these scales are found to communicate interval properties to the survey respondents, the data produced is assumed to be interval-scaled (Madsen, 1989; Schertzer and Jerome, 1985, Jaccard and Wan, 1996; Chong, 2009).

4.5.2 Perceived goal attainment, perceived velocity and team learning behavior

Perceived Goal attainment and perceived velocity are measured based on four items (i.e. 2 for each variable). The items used in this study are adapted from Huang and Zhang (2011). Team learning behaviour measurements are adopted from Edmonson (1999) and four items are used for the measurement. Similar to the justifications in 4.5.1, 7 Likert Scales are used to measure the items.

4.5.3 Motivation to Learn EHR, Behavioural intention and Actual use

The motivation to learn EHR is based on a single item measuring how motivated the users are in learning the EHR system in the company (Huang and Zhang, 2011). Behavioural intention and actual use are based on Venkatesh et al. (2003) where behavioural intention is measured based on 3 items using a 7-point Likert Scale, where 1 = strongly disagree and 7 = strongly agree, while Actual Use measures how much time the users spent in using the system every day ranging from 1 hour to more than 9 hours. Originally, the measurement aims to let users report the time based on how many minutes/hours they spend per day, and filling the estimated time rather than checking the 1-9 hour categories. However, based on the pilot study findings, users were quite confused when they are asked to fill in the time duration themselves, and they would prefer a category of time duration in hours from which they can choose. Table 4.2 provides the measurement items, source and scales of the constructs. As shown in the table, questions related to behavioural intention was only measured in questionnaire distributed in T1. Actual Use on the other hand, was only measured in questionnaires distributed at T2 and T3. All other questions were distributed for T1, T2 and T3.

Table 4.2 Constructs, measurement items, source and scales

Construct	**Measurement items**	**Source**	**Scale**	**Time period where questions are collected**
Behavioural Intention	• I intend to use e-Mediviron in the next 6 months.	Venkatesh et al. (2003)	7 Point Likert Scale	T1 only

	• I predict I would use e-Mediviron in the next 6 months. • I plan to use e-Mediviron in the next 6 months.			
Actual Use	• How much time do you spend using e-Mediviron2 every day?	Venkatesh et al. (2003)	9 point scales ranging from 1 hour to more than 9 hours	T2 and T3
Motivation to learn	• How motivated are you to learn using e-Mediviron 2 successfully? •	Own scale	7 Point Likert Scale	T1, T2 and T3
Performance Expectancy	• I would find e-Mediviron 2 to be useful in my job. • Using e-Mediviron 2 would enable me to accomplish tasks more quickly. • Using e-Mediviron 2 would increase my productivity. • If I use e-Mediviron 2, I will increase my chances of getting a raise.	Venkatesh et al. (2003)	7 Point Likert Scale	T1, T2 and T3
Effort Expectancy	• My interaction with e-Mediviron 2 would be clear and understandable. • It would be easy for me to become skillful at using e-Mediviron 2. • I would find e-Mediviron 2 easy to use. • Learning to use e-Mediviron 2 would be easy for me.	Venkatesh et al. (2003)	7 Point Likert Scale	T1, T2 and T3
Social Influence	• People who are important to me think that I should use e-	Venkatesh et al. (2003)	7 Point Likert Scale	T1, T2 and T3

	Mediviron 2. • People who influence my behavior think that I should use e-Mediviron 2. • People whose opinions that I value prefer that I use e-Mediviron 2.			
Facilitating Conditions	• I have the resources necessary to use e-Mediviron 2. • I have the knowledge necessary to use e-Mediviron 2. • E-Mediviron 2 is not compatible with other systems I use. • A specific person (or group) is available for assistance with system difficulties.	Venkatesh et al. (2003)	7 Point Likert Scale	T1, T2 and T3
Team Learning Behaviour	• We regularly take time to figure out ways to improve our team's work processes. • This team tends to handle differences of opinion privately or off-line, rather than addressing them directly as a group. • Team members go out and get all the information they possibly can from others – such as customers, or other parts of the organization. • This team frequently seeks new information that leads us to make important changes.	Edmonson, (1999)	7 Point Likert Scale	T1, T2 and T3

Perceived Attainability	• How likely do you think it is that you will be able to use perfectly well e-Mediviron 2? • How difficult does it seem for you to learn how to use e-Mediviron 2?	Adapted from Huang and Zhang (2011), Zhang and Huang (2010)	7 Point Likert Scale	T1, T2 and T3
Perceived Velocity	• Compared to your colleagues, when do you think you will be able to use perfectly well e-Mediviron 2? • How soon do you think you will be able to use perfectly well e-Mediviron 2?	Adapted from Huang and Zhang (2011), Zhang and Huang (2010)	7 Point Likert Scale	T1, T2 and T3

4.6 Sampling and data collection procedure

This unit of this study is healthcare professionals (e.g. doctors, para-professionals, and administrators) which is consistent with Venkatesh et al. (2011). Similar to studies in the past that have been used to develop UTAUT (Venkatesh et al., 2003) and other technology adoption studies (Chong et al., 2015), this research work is conducted with a large medical group of clinics that is implementing an EHR system known as e-Mediviron. This research work, together with Mediviron Group of Clinics, is used to collect data from its employees in order to understand their EHR adoption decisions.

Mediviron Group of Clinics is one of the largest clinics with approximately 200 clinics located in different states in Malaysia. They have 1300 employees (i.e. paraprofessionals and administrators) and 250 doctors. Founded in 1984, they provide comprehensive primary care medical services to all their clients, from the general public to the corporate and statutory bodies in Malaysia. They are also one of the pioneers in the field of Occupational Health and Safety Practices in Malaysia, having provided consultancy to many governmental departments, professional organizations and industrial corporations since 1984.

This research's data collection occurred in conjunction with the group's implementation of a enterprise wide EHR solution, which they termed the e-Mediviron system. The e-mediviron system supported all aspects of patient care such as patient health information, health records, treatment plans, billing and follow-up. The system was developed by a leading Singapore software vendor and was customized to fit the needs of the group. The employees from the group

were briefed that this research is part of a PhD study, and names and details of employees participating in the survey will be kept private and confidential. This assurance is to ensure that employees will provide honest feedback. Ethics application was also applied and approved by University of Nottingham's research ethics committee. In implementing the system, training sessions that are customized for the needs of the specific group of users were offered by the vendor before the rollout of the system. There were multiple sessions that took place with each session lasting from two to four hours, recorded over the course of a month. In order to minimize training variability, the trainers use identical training scripts to deliver the instructions. E-Mediviron was implemented after all the training sessions were completed. The procedures involved in the training and the rollout of the system was in-lined with the practise conducted by Venkatesh et la. (2011).

Adopting the longitudinal data collection approach by Venkatesh et al. (2011) and Venkatesh and Davis (2000), this survey was conducted 3 times over a period of 5 months. Table 4.3 below provides an overview of the data collection timeline.

Table 4.3 Data collection plan

T1: Month 1 (Pre-implementation)	T2: Month 2-3 (Implementation)	T3: Month 4-5 (Sustained Implementation)
Training takes place with several sessions made available to employees. After training, the first survey was conducted where questionnaire was distributed and collected. System roll out after the training.	E-Mediviron is available online for employees to access. At the end of month 3, a second survey was distributed and collected.	At the end of month 5, a third survey was distributed and responses collected.

4.7 Sampling results

With the help of Mediviron headquarters and the company's managing director, a survey questionnaire was distributed to 1000 employees in 195 clinics that belong to Mediviron. The pre-implementation survey resulted in 520 returned surveys. For T2 (Month 2-3), the 520 respondents who completed the surveys were sent the second questionnaire, and 210 surveys were returned. In T3 (Month 4-5), the 210 survey respondents in T2 were sent the third questionnaire, and 182 surveys were returned. In order to track the respondent, the employees full name and employee numbers were collected, and an ID is assigned to the data. Once the data and ID number are entered, the name and employee numbers are removed from the database in order to ensure the confidentiality of the respondents.

Researchers such as Chin (1998), Hair et al. (2016) and Hair et al. (2017) recommend PLS users to use the "rule of 10" guideline in determining the minimum sample size for using PLS-SEM. This rule states that there should be

at least 10 cases per measured variable for the larger of (1) the number of indicators in the largest latent factor block, or (2) the largest number of incoming causal arrows for any latent variable in the model.

Based on the conceptual model proposed in this research, the largest number of incoming causal arrows for the latent variable (i.e. motivation to learn) is seven, thus the minimum number of samples required for this study is 70. Given that the number of data collected at all three stages (i.e. 520, 210 and 182) all exceed 70, the sample size satisfied the rule of 10 guideline. The demographics of the respondents are shown below in Table 4.4 below.

Table 4.4 Demographic profile of respondents

T1 (Month 1: Pre-implementation)

Demographic Information	Numbers	Percentage
Doctors	221	42.50
Administrators	150	28.85
Para-Professionals	149	28.65
Average Age	28.49	
Gender Male Female	 226 294	 43.46 56.54
Education High School Diploma or equivalent University qualifications (e.g. Bachelors and above)	 112 156 252	 21.54 30.00 48.46

T2 (Month 2-3: Implementation)

Demographic Information	Numbers	Percentage
Doctors	84	40.00
Administrators	64	30.48
Para-Professionals	62	29.52
Average Age	27.56	
Gender Male Female	 90 120	 42.86 57.14
Education High School Diploma or equivalent University qualifications (e.g. Bachelors and above)	 30 70 110	 14.29 33.33 52.38

T3 (Month 4-5: Sustained Implementation)

Demographic Information	Numbers	Percentage
Doctors	76	41.76
Administrators	54	29.67
Para-Professionals	52	28.57
Average Age	27.49	
Gender Male Female	 80 102	 43.96 56.04
Education High School Diploma or equivalent University qualifications (e.g. Bachelors and above)	 22 60 100	 12.09 32.97 54.95

4.8 Summary of Chapter

This study develops a questionnaire to collect data to examine the hypotheses proposed in Chapter 3. In this chapter, the rationale for selecting the survey methodology is discussed. This chapter also describes the research procedures employed in this research. The survey questionnaire variables are also presented

in this chapter. The minimum sample sizes to analyse the research models explained. The next chapter will present the data analysis of this research using PLS-SEM to examine the data and test the hypotheses proposed in Chapter 3.

CHAPTER 5 DATA ANALYSIS

5.1 Introduction

This chapter will present how PLS-SEM was employed to analyse the measurement and structural model. Internal consistency, convergent validity and discriminant validity are conducted and discussed. This is followed by the assessment of the structural model. A bootstrapping method was applied to test the significant levels of the results. This research applied 5,000 bootstrap samples as recommended by Hair et al. (2016). This satisfied the recommendation by Hair et al. (2016), which stated that the number of bootstrap samples must be greater than or at least equal to the number of valid observations of the data.

5.2 Procedure for applying PLS-SEM

This research employs the recommendations and procedures by Hair et al. (2016), Hair et al. (2017) and Chong et al. (2018) in employing a systematic procedure for applying PLS-SEM. This is shown in Figure 5.1.

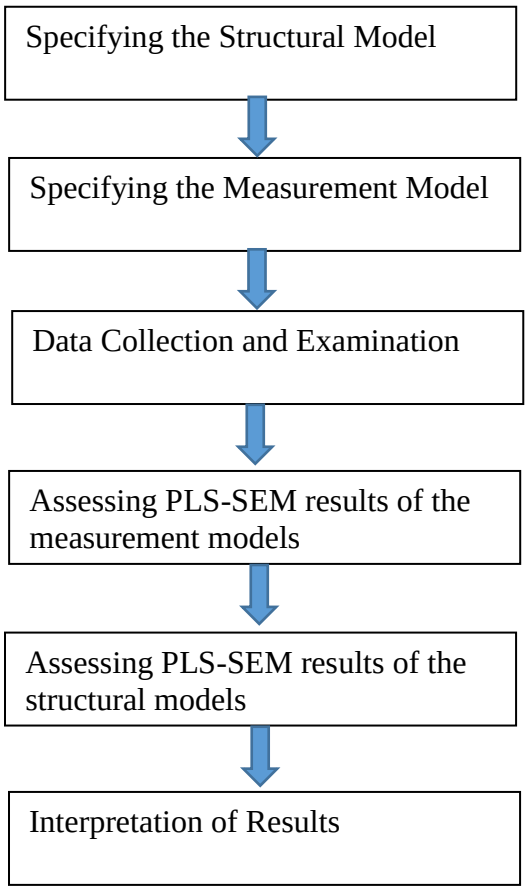


Figure 5.1 Adapted from procedures for employing PLS-SEM (Hair et al., 2017)

The next sections present the assessment of the PLS-SEM measurement and structural model.

5.3 Assessment of measurement model

As stated by Hair et al. (2016), the evaluations of the measurement models in PLS-SEM involve the following tests: Internal consistency (composite reliability), indicator reliability, Convergent validity (average variance extracted)

and discriminant validity. The rule of thumb for evaluating the reflective measurement model is in Table 5.1 below:

Table 5.1 Rule of thumb for evaluating reflective measurement model

Measurement tests	**Rules**
Internal consistency reliability	Composite reliability should be more than 0.70
Indicator reliability	The indicator's loadings should be higher than 0.70. However, indicators with outer loadings of between 0.40 and 0.70 should only be considered for removal if upon deleting them, composite reliability and AVE will increase above the suggested threshold value.
Convergent validity	AVE should be greater than 0.50
Discriminant validity	An indicator's outer loadings on a construct should be higher than all its cross loadings with other constructs. The square root of the AVE of each construct should be higher than its highest correlation with any other constructs (Fornell Larcker criterion)

Composite reliability is frequently employed as the estimate of internal consistency reliability. The traditional way to measure internal consistency is using Cronbach's alpha**,** which estimates reliability based on the inter-correlations of the indicators, and assumes that all of the indicators are equally reliable. However, this is suggested to be not suitable when being applied to PLS-SEM since individual reliability is used to prioritize indicators (Ringle et al., 2009). Furthermore, Cronbach's alpha is sometimes criticized by scholars such as Hair et al. (2016) and Hair et al. (2017) as being too sensitive to the number of items in a dimension, which result in posing a threat to

underestimating internal reliability. As such, it is argued that composite reliability, which does not assume equal reliability among indicators, is considered to be a more suitable estimate of internal reliability for PLS-SEM. Composite reliability examines internal consistency reliability by employing the standardized outer loading (λ_i) of the indicator i of a specific construct, which is calculated with the following formula from Chin (1998):

$$CompositeReliability = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum(1 - \lambda_i{}^2)}$$

As stated in Table 5.2 (a-c), composite reliabilities of 0.70 or higher are considered to indicate sufficient levels of internal consistency. As shown in Table 5.2 a-c, the composite reliabilities of all constructs were greater than the threshold, therefore confirming the satisfactory internal consistency of the measurement model (Hair et al., 2016).

Table 5.2a Reliability and validity analyses for T1

Construct	Items	Outer Loadings	Composite Reliability	AVE
Perceived goal attainment	Att1	0.960	0.925	0.860
	Att2	0.769		
Behavioral Intention	BI1	0.886	0.929	0.813
	BI2	0.926		
	BI3	0.893		
Effort Expectancy	EE1	0.900	0.783	0.502
	EE2	0.764		
	EE3	0.793		
	EE4	0.821		
Facilitating Conditions	FC1	0.854	0.853	0.660
	FC2	0.803		
	FC3	0.778		
Performance Expectancy	PE1	0.865	0.896	0.684
	PE2	0.858		
	PE3	0.817		
	PE4	0.764		
Social Influence	SI1	0.876	0.896	0.683
	SI2	0.861		
	SI3	0.739		
	SI4	0.823		
Team Learning Behavior	TLB1	0.851	0.881	0.711
	TLB2	0.838		
	TLB3	0.841		
Perceived Velocity	Vlc1	0.936	0.860	0.756
	Vlc2	0.918		

Table 5.2b Reliability and validity analyses for T2

Construct	Items	Outer Loadings	Composite Reliability	AVE
Perceived goal attainment	Att1	0.964	0.920	0.851
	Att2	0.880		
	BI3	0.893		
Effort Expectancy	EE1	0.796	0.855	0.528
	EE2	0.766		
	EE3	0.793		
	EE4	0.734		
Facilitating Conditions	FC1	0.785	0.855	0.598
	FC2	0.824		
	FC3	0.723		
	FC4	0.849		
Performance Expectancy	PE1	0.933	0.881	0.650
	PE2	0.758		
	PE3	0.700		
	PE4	0.821		
Social Influence	SI1	0.806	0.801	0.504
	SI2	0.797		
	SI3	0.700		
	SI4	0.724		
Team Learning Behavior	TLB1	0.768	0.829	0.548
	TLB2	0.776		
	TLB3	0.769		
	TLB4	0.722		
Perceived Velocity	Vlc1	0.741	0.777	0.643
	Vlc2	0.935		

Table 5.2c Reliability and validity analyses for T3

Construct	Items	Outer Loadings	Composite Reliability	AVE
Perceived goal attainment	Att1	0.722	0.794	0.661
	Att2	0.895		
Effort Expectancy	EE1	0.795	0.859	0.605
	EE2	0.823		
	EE3	0.822		
	EE4	0.766		
Facilitating Conditions	FC1	0.875	0.878	0.645
	FC2	0.849		
	FC3	0.706		
	FC4	0.771		
Performance Expectancy	PE1	0.711	0.849	0.584
	PE2	0.763		
	PE3	0.809		
	PE4	0.771		
Social Influence	SI1	0.806	0.883	0.654
	SI2	0.767		
	SI3	0.849		
	SI4	0.81		
Team Learning behavior	TLB1	0.836	0.895	0.74
	TLB2	0.914		
	TLB3	0.827		
Perceived Velocity	Vlc1	0.912	0.907	0.83
	Vlc2	0.911		

Construct validity examines if the items capture the concepts that the constructs intend to measure (Hair et al., 2016). This is typically examined using convergent validity and discriminant validity. Convergent validity is the degree to which an indicator is positively correlated with the remaining indicators in the same construct. In this research where a reflective measurement is developed, indicators measuring the same construct should converge or share a large portion of variance because they are being treated as different approaches to measure the same variable (Hair et al., 2016). As such, the indicators' standardized outer loadings and the AVE are considered as establishing convergent validity.

Indicator reliability is confirmed when the outer loadings of a construct are high. This is due to reason that what are captured by the construct from the corresponding indicators will have much in common. The main rule for this is that the standardized outer loadings should be more than 0.70 (Chong et al., 2017). As shown in Table 5.2 a-c, the outer loadings of the reflective indicators are all more than 0.70, thus confirming indicator reliability.

AVE is also applied to test the convergent validity at the construct level, AVE is equivalent to the construct's **communality** by measuring the grand mean value of the standardized loadings of the indicators in a construct (Hair et al., 2016). AVE is calculated by on the formula below:

$$AVE = \frac{\sum {\lambda_i}^2}{\sum {\lambda_i}^2 + \sum\left(1 - {\lambda_i}^2\right)}$$

When AVE is more than 0.50, it confirms that the construct explains more than 50% of the variance in the associated indicators. Once again, table 5.3 (a-c) shows that the values for all AVEs of the constructs are greater than 0.50, which confirmed convergent validity.

Discriminant validity tests the extent to which a construct is distinct from other constructs in the same model. This helps ensure that a construct captures the unique concepts that are not measured by other constructs. As suggested by Hair et al. (2016), in order to establish discriminant validity of the reflective measurements, the Fornell-Larcker criterion and cross-loadings are two measures that should be employed. The Fornell-Larcker criterion stated that a construct should share more variance with its indicators than the variance shared

with other constructs in the same model. This means that in statistical terms, it is expressed that the square root of a construct's AVE should exceed the highest correlation it has with any other construct. As shown in Tables 5.3 (a-c), the square roots of the AVEs (figures on the diagonal and bold) are all greater than the correlations among the constructs (figures off the diagonal), thus confirming discriminant validity

Table 5.3a Discriminant Validity (T1)

	1	2	3	4	5	6	7	8	9	10	11	12
Age	**1**											
Perceived Goal Attainment	0.07	**0.927**										
Behavioral Intention	0.032	0.621	**0.902**									
Effort Expectancy	0.146	0.171	0.235	**0.709**								
Experience	-0.037	-0.036	-0.034	0.076	**1**							
Facilitating Conditions	-0.044	-0.219	-0.203	-0.313	0.002	**0.812**						
Gender	-0.073	-0.162	-0.075	-0.045	-0.039	0.051	**1**					
Motivation	0.028	0.708	0.657	0.159	-0.052	-0.216	-0.095	**1**				
Performance Expectancy	0.068	0.455	0.494	0.251	-0.039	-0.47	-0.106	0.439	**0.827**			
Social Influence	-0.107	-0.011	0.016	0.002	0.17	-0.033	0.002	0.105	0.032	**0.826**		
Team Learning Behavior	0.091	0.264	0.308	0.244	0.04	-0.236	-0.016	0.192	0.294	-0.074	**0.843**	
Perceived Velocity	0.149	0.283	0.311	0.293	-0.072	-0.48	-0.013	0.233	0.412	0.057	0.296	**0.87**

Table 5.3b Discriminant Validity (T2)

	1	2	3	4	5	6	7	8	9	10	11	12	13
Actual use	**1**												
Age	-0.075	**1**											
Perceived Goal Attainment	0.37	-0.05	**0.923**										
Effort Expectancy	0.509	-0.087	0.445	**0.726**									
Experience	0.012	0.164	0.008	0.009	**1**								
Facilitating Conditions	0.405	-0.127	0.461	0.471	-0.106	**0.773**							
Gender	-0.008	-0.241	0	-0.057	-0.069	-0.035	**1**						
Motivation	0.131	0.027	-0.3	0.058	-0.063	0.03	-0.111	**1**					
Performance Expectancy	0.202	-0.09	0.428	0.311	0.028	0.562	-0.007	-0.059	**0.808**				
Social Influence	0.32	-0.08	0.356	0.407	0.14	0.377	0.081	0.074	0.262	**0.71**			
Team Learning Behaviour	0.42	0.047	0.595	0.452	0.092	0.518	0.045	-0.173	0.451	0.494	**0.74**		
Performances	0.212	-0.184	0.16	0.233	-0.11	0.286	-0.038	0	0.176	0.185	0.137	**1**	
Perceived Velocity	-0.081	0.038	-0.022	-0.127	0.088	-0.051	0.171	-0.163	0.063	0.135	0.108	-0.088	**0.802**

Table 5.3c (T3)

	1	2	3	4	5	6	7	8	9	10	11	12	13
Actual use	**1**												
Age	-0.043	**1**											
Perceived Goal Attainment	-0.017	0.017	**0.813**										
Effort Expectancy	0.052	0.075	0.172	**0.778**									
Experience	0.205	0.025	0.066	0.019	**1**								
Facilitating Conditions	0.153	-0.128	0.199	0.302	0.138	**0.803**							
Gender	-0.118	-0.105	0.087	-0.075	-0.053	-0.057	**1**						
Motivation	0.306	-0.091	0.273	0.317	0.037	0.476	-0.052	**1**					
Performance Expectancy	0.045	-0.161	0.133	0.385	0.105	0.476	-0.069	0.415	**0.764**				
Social Influence	0.622	-0.084	-0.169	-0.07	0.088	-0.036	-0.09	0.037	-0.164	**1**			
Team Learning Behaviour	0.115	0.002	0.279	0.452	-0.001	0.41	-0.012	0.572	0.535	-0.062	**0.808**		
Performances	0.345	-0.092	0.086	0.374	0.059	0.53	-0.033	0.537	0.476	0.11	0.57	**0.86**	
Perceived Velocity	0.076	-0.06	0.213	0.422	-0.044	0.341	0.016	0.537	0.456	-0.103	0.584	0.381	**0.911**

5.4 Assessment of structural model

In this section, the proposed conceptual model and hypotheses are examined using PLS-SEM. The standardized path coefficients and the corresponding significance levels (two-tailed tests) are presented, as well as the amount of variance explained (R^2 and adjusted R^2). All SEM models were run in the analysis in order to test data collected during T1, T2 and T3. This allows for examination if users' perceptions or views change during the course of using the eMediviron system. Furthermore, data at T2 and T3 will show how the relationships may change during the implementation and post implementation of EHR. The result of the model is shown in Table 5.4.

5.4.1 Testing of conceptual model and hypotheses

In order to examine the conceptual model developed in this study in a systematic approach, the results will be discussed based on the hypotheses and time period (i.e. T1, T2 and T3) proposed in Chapter 3. As shown in the result in Table 5.4, for H1a, performance expectancy has a positive and significant influence ($\beta = p<0.05$) on the behavioural intention to use EHR. Thus, this study can support H1a. For H1b, the result shows that performance expectancy has a positive and significant influence on motivation to learn ($\beta = 0.130$, $p<0.001$) during T1, and during T2, continues to exhibit significant influence ($\beta = 0.195$, $p<0.05$), but it has no significant relationship during T3 ($\beta = -0.054$, $p>0.05$). This shows that performance expectancy does influence motivation to learn (i.e. T1 and T2), but over time, the influence of the predictor reduces and is no longer significant by the time it reaches 4-5 months of system use. This result confirms H1b. Performance expectancy is found to have no significant relationship with

actual use of EHR at both T2 (β =0.050, p>0.05) and T3 (β =-0.160, p>0.05), thus H1c is rejected.

Effort Expectancy is found to have a significant and positive relationship with behavioural intention to use EHR (β =0.076, p<0.05) motivation to learn EHR (β =0.130, p>0.05), thus H2a is supported. Effort expectancy, however, was found to have no significant influence on the motivation to learn EHR in all time periods T1 (β =0.023, p>0.05), T2 (β =0.074, p>0.05) and T3 (β =-0.073, p>0.05). Therefore, H2b is not supported. Similarly, effort expectancy was also found to have no significant influence on the actual use of EHR, i.e. T2 (β =0.107, p>0.05) and T3 (β =-0.073, p>0.05). Therefore, H2c is also not supported.

Social influence is found to have no significant relationship with behavioural intention to use EHR (β =-0.028, p>0.05), thus H3a is not supported. Social influence is found to have a significant and positive relationship with motivation to learn EHR during T1 (β =0.117, p<0.01) and T3 (β =0.236, p<0.05). However, it has no significant relationship during T2 (β =-0.054, p>0.05). Thus H3b is partially supported. Social influence is also found to have no significant relationship with the actual use of EHR at T2 (β =-0.073, p>0.05) and T3 (β =-0.093, p>0.05), therefore H3c is not supported.

This research found that facilitating conditions have a significant and positive relationship with behavioural intention to use EHR (β =0.105, p<0.05). Therefore, H4a is supported by the results. However, facilitating conditions do not have a significant and positive relationship with actual use of EHR at both T2 and T3 (β =-0.073, p>0.05) and (β =-0.116, p>0.05). As such, H4b is rejected.

Facilitating conditions is found to have no significant relationship with actual use of EHR at T2 (β =-0.012, $p>0.05$) and T3 (β =-0.116, $p>0.05$). Therefore, H4c is also not supported

H5a in this research is supported as perceived goal attainment has a positive and significant relationship with behavioural intentions to use EHR (β =0.217, $p<0.001$). Perceived attainment is found to have a positive and significant relationship with motivation to learn EHR during T1 (β =-0.654, $p<0.001$) and T2 (β =0.274, $p<0.05$), while the relationship is not significant at T3 (β =0.125, $p>0.05$). These findings show that the effects of perceived goal attainment on motivation to learn EHR gradually reduces over time, thus supporting H5b. The result also shows that perceived goal attainment does not have a significant relationship with actual use of EHR at T2 (β =0.002, $p>0.05$) and T3 (β =-0.104, $p>0.05$), thereby supporting H5c.

Perceived velocity is found to have a significant and positive relationship with behavioural intentions to use EHR (β =0.081, $p<0.05$), thus supporting H6a. Perceived velocity does not have a positive or significant relationship with motivation to learn at T1 (β =-0.025, $p>0.05$), but it has a positive and significant relationship with motivation to learn at T2 (β =0.216, $p<0.05$) and T3 (β =0.312, $p<0.001$). This shows that the relationship increases from T1 to T3 where the influence gets stronger, and this confirms H6b. Perceived velocity, however, is found to have no significant influence on actual use of EHR at T2 (β =0.193, $p>0.05$) and T3 (β =-0.059, $p>0.05$). Therefore, H6c is rejected.

Team learning behaviour is found to have a positive and significant relationship with behavioural intention to use EHR (β =0.101, $p<0.05$), and this confirms

H7a. However, team-learning behaviour only has a positive and significant relationship with motivation to learn EHR at T3 (β =0.200, $p<0.05$). During T1 and T2, both relationships are not confirmed (β =-0.001, $p>0.05$) and (β =-0.082, $p>0.05$). Therefore, H7b is only partially supported. Team learning behaviour is found to have significant and positive influence on the actual use of EHR at both T2 (β =0.338, $p<0.05$) and T3 (β =0.293, $p<0.05$), thus confirming H7c.

Motivation to learn EHR is found to have positive and significant relationship on the behavioural intention to use EHR (β =0.396, $p<0.05$), as well as the actual use of EHR at both T2 (β =0.243, $p<0.05$) and T3 (β =0.295, $p<0.05$). Therefore H8a and H8b are supported.

For the moderators proposed, most of the effect is confirmed only at the actual use stage and for motivation to learn EHR. The majority of these effects are found during months 2-3 of the EHR implementation. During pre-implementation stage, all the moderating relationships were found to be not significant. Gender is found to moderate effort expectancy at T2 (β =0.205, $p<0.05$) and T3 (β =0.249), $p<0.05$,) and performance expectancy at T3 (β =-0.202, $p<0.05$), thus partially supporting H9a and H9b.

Age is found to have no moderating effect on the relationships between performance expectancy and motivation to learn to use EHR, effort expectancy and motivation to learn to use EHR, social influence and motivation to learn to use EHR, and facilitating condition and motivation to learn to use EHR at T1, T2 and T3. Therefore, H10a, H10b, H10c and H10d are all not supported. Facilitating conditions is also found to be moderated by user experience during T2, therefore partially confirming H11c. Perceived goal attainment is also found

to have not moderating effect on effort expectancy and performance expectancy at both T1, T2 and T3. Therefore, H12a, H12b, H12c and H12d are all not supported. Perceived velocity is found to moderate performance expectancy in users' motivation to learn EHR (β =0.206, $p<0.05$), thus partially confirming H13a.

As stated by Hair et al. (2016), the most common method applied to evaluate the structural model is the coefficient of determination (R^2 value). R^2 ranged from 0 to 1, where higher levels indicate higher levels of predictive accuracy (Hair et al., 2016). In general, there is no acceptable rule of thumb for acceptable R^2 values, since this is highly dependent on the complexity of the model as well as the discipline of study. However, in behavioural studies, R^2 values of 0.20 and above are considered high (Tan and Ooi, 2018). Even so, if only R^2 is used, problems sometimes arise. For example, adding non-significant variables constructs to the structural model that are correlated to the endogenous latent variable can lead to an increase in R^2. Using only R^2 could result in a bias towards selecting a model that contains many exogenous constructs (Hair et al., 2016). Besides using R^2, it is also suggested that researchers should also apply an adjusted R^2 value, and this can be used as a criterion to avoid bias towards models that are more complex. The findings revealed that R^2 values for motivation to learn EHR are 0.545 (adjusted R^2 of 0.523) at T1, 0.367 (adjusted R^2 of 0.367) at T2, and 0.185 at T1 (adjusted R^2 of 0.132) at T3. The R^2 values for behavioural intention to use EHR are 0.540 (adjusted R^2 of 0.530) at T1, acceptance of EHR are 0.425 (adjusted R^2 of 0.351) at T2, and 0.575 (adjusted R^2 of 0.510) at T3. These adjusted R^2 values are acceptable for social science research, and this shows that in general, the models have quite high predictive

accuracy in determining healthcare professionals' motivations to learn EHR and behavioural intention to accept and use EHR

Table 5.4 SEM results (T1-T3)

T 1 (Month 1: Pre-Implemetation)			**T2 (Month 2-3)**			**T3 (Month 4-5)**		
	Beta	**P-values**		**Beta**	**P-values**		**Beta**	**P-values**
Perceived Attainment -> Motivation	**0.654**	**0**	**Perceived Attainment -> Motivation**	**0.274**	**0.001**	Perceived Attainment -> Motivation	0.125	0.075
Perceived Velocity -> Motivation	-0.025	0.514	**Perceived Velocity -> Motivation**	**0.216**	**0.049**	**Perceived Velocity -> Motivation**	**0.312**	**0.000**
Team Learning Behavior -> Motivation	-0.001	0.974	Team Learning Behaviour -> Motivation	-0.082	0.306	**Team Learning Behavior -> Motivation**	**0.200**	**0.024**
Effort Expectancy -> Motivation	0.023	0.563	Effort Expectancy -> Motivation	0.074	0.543	Effort Expectancy -> Motivation	-0.073	0.406
Performance Expectancy -> Motivation	**0.13**	**0**	**Performance Expectancy -> Motivation**	**0.195**	**0.031**	Performance Expectancy -> Motivation	-0.054	0.535
Social Influence -> Motivation	**0.117**	**0.001**	Social Influence -> Motivation	-0.054	0.584	**Social Influence -> Motivation**	**0.236**	**0.023**
Facilitating Conditions -> Motivation	-0.019	0.631	Facilitating Conditions -> Motivation	0.089	0.197	**Facilitating Conditions -> Motivation**	**0.209**	**0.004**
Perceived Attainment -> Behavioral Intention	**0.217**	**0**	Perceived Attainment -> Actual Use	0.002	0.984	Perceived Attainment -> Actual Use	-0.104	0.313
Perceived Velocity -> Behavioral Intention	**0.081**	**0.035**	Perceived Velocity -> Actual	0.193	0.063	Perceived Velocity -> Actual Use	-0.059	0.517
Effort Expectancy -> Behavioral Intention	**0.076**	**0.016**	Effort Expectancy -> Actual Use	0.107	0.190	Effort Expectancy -> Actual Use	0.005	0.960
Performance Expectancy -> Behavioral Intention	**0.194**	**0**	Performance Expectancy -> Actual Use	0.050	0.531	Performance Expectancy -> Actual Use	-0.160	0.109
Social Influence -> Behavioral Intention	-0.028	0.473	Social Influence -> Actual Use	0.044	0.611	Social Influence -> Actual Use	-0.093	0.378
Facilitating Conditions -> Behavioral Intention	**0.105**	**0.005**	Facilitating Conditions -> Actual Use	-0.102	0.089	Facilitating Conditions -> Actual Use	-0.116	0.195
Team Learning Behavior -> Behavioral Intention	**0.101**	**0.002**	**Team Learning Behaviour -> Actual Use**	**0.388**	**0.000**	**Team Learning Behavior -> Actual Use**	**0.293**	**0.006**
Motivation -> Behavioral Intention	**0.396**	**0**	**Motivation -> Actual Use**	**0.243**	**0.001**	**Motivation -> Actual Use**	**0.295**	**0.004**
Age*Effort Expectancy -> Motivation	-0.004	0.913	Age*Effort Expectancy -> Motivation	-0.004	0.973	Age*Effort Expectancy -> Motivation	-0.049	0.640
Age*Performance Expectancy -> Motivation	-0.042	0.205	Age*Facilitating Conditions -> Motivation	-0.073	0.277	Age*Facilitating Conditions_ -> Motivation	-0.105	0.250
Age*Social Influence-> Motivation	0.05	0.145	Age*Performance Expectancy -> Motivation	0.002	0.986	Age*Performance Expectancy -> Motivation	-0.023	0.833
Age*Facilitating Conditions -> Motivation	-0.004	0.891	Age*Social Influence -> Motivation	0.066	0.666	Age*Social Influence -> Motivation	0.180	0.081
Experience*Effort Expectancy -> Motivation	-0.057	0.21	Experience*Effort Expectancy -> Motivation	-0.028	0.703	Experience*Effort Expectancy -> Motivation	-0.103	0.342
Experience*FC -> Motivation	-0.052	0.199	Experience*Facilitating Conditions -> Motivation	0.149	0.029	Experience*Facilitating Conditions -> Motivation	0.002	0.981
Experience*Social Influence -> Motivation	0.006	0.857	Experience*Social Influence -> Motivation	-0.091	0.332	Experience*Social Influence -> Motivation	0.053	0.769
Gender*Effort Expectancy-> Motivation	0.037	0.299	**Gender*Effort Expectancy -> Motivation**	**0.205**	**0.023**	**Gender*Effort Expectancy -> Motivation**	**0.249**	**0.008**
Gender*Performancce Expectancy -> Motivation	0.012	0.729	**Gender*Performance Expectancy -> Motivation**	**-0.202**	**0.019**	Gender*Performane Expectancy -> Motivation	0.008	0.918
Gender*Social Influence-> Motivation	0.039	0.251	Gender*Social Influence -> Motivation	-0.063	0.461	Gender*Social Influence -> Motivation	-0.062	0.497
Perceived Attaintment*Effort Expectancy -> Motivation	0.036	0.329	Perceived Attainment*Effort Expectancy -> Motivation	0.078	0.371	Perceived Attainment*Effort Expectancy -> Motivation	-0.090	0.340
Perceived Attainment*Performance Expectancy -> Motivation	-0.007	0.804	Perceived Attainment*Performance Expectancy -> Motivation	-0.124	0.160	Perceived Attainment*Performance Expectancy -> Motivation	0.034	0.617
Perceived Velocity*Effort Expectancy -> Motivation	0.02	0.555	Perceived Velocity*Effort Expectancy -> Motivation	-0.124	0.157	Perceived Velocity*Effort Expectancy -> Motivation	0.071	0.294
Perceived Velocity*Performance Expectanccy -> Motivation	-0.005	0.929	**Perceived Velocity*Performance Expectancy -> Motivation**	**0.206**	**0.023**	Perceived Velocity*Performance Expectancy_ -> Motivation	-0.121	0.055
	R^2	Adjusted R^2		R^2	Adjusted R^2		R^2	Adjusted R^2
Motivation	0.545	0.523	Actual Use	0.367	0.339	Actual Use	0.185	0.132
Behavioral Intention	0.540	0.530	Motivation	0.425	0.351	Motivation	0.575	0.510

5.4.2 Examining Venkatesh et al. (2003) original UTAUT's application in behavioural intention/actual use of EHR

In order to compare the extended UTAUT which include motivation to learn, perceived velocity and goal attainment employed in this study with the outcomes of the original UTAUT proposed by Venkatesh (et al., 2003), this research also tested the UTAUT model as shown in Figure 5.2 and Figure 5.3.

Figure 5.2 UTAUT employed during T1 (Pre-implementation)

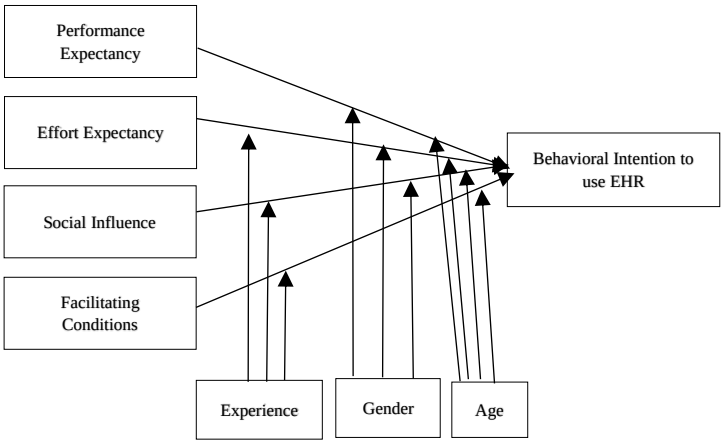


Figure 5.3 UTAUT employed during T2 (Implementation) and T3 (Sustained implementation)

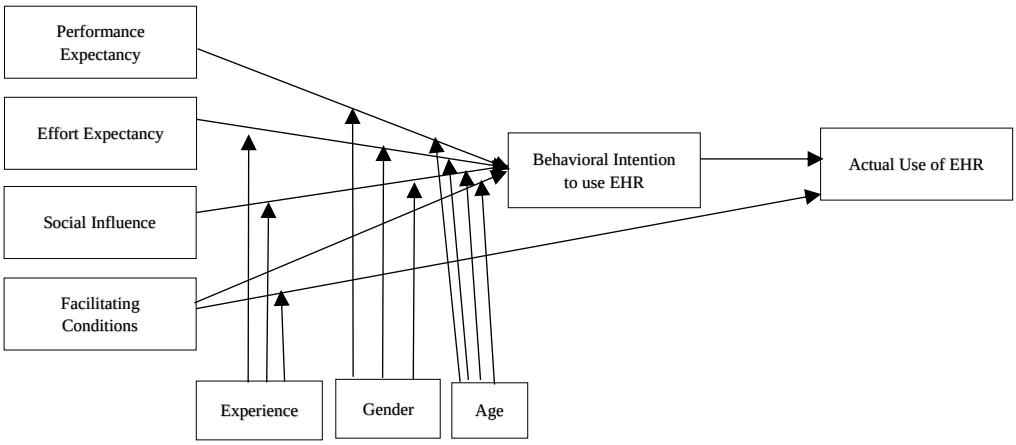


Table 5.5 provides a summary of the results of testing the UTAUT. The R^2 values in the UTAUT models presented in Figure 5.2 and Figure 5.3 will be used to compare with the R^2 values of the extended UTAUT proposed in this research to see which models perform better.

As shown in table 5.5, the adjusted R^2 values for behavioural intention are 0.256, 0.250 and 0.486 for T1, T2, and T3. The adjusted R^2 values for actual use of EHR are 0.194 and 0.328. This shows that when applying the full replication of UTAUT to the context of this study, the R^2 are much lower than the extended UTAUT that is applied in this research. T3 is also a much stronger model when compared to T1 and T2, meaning that UTAUT seems to be more relevant after a 4-5 month implementation period of e-Mediviron system. Furthermore, this research also proposed a path relationship between facilitating conditions and behavioural intentions, which is not proposed in the original UTAUT. However, this path is significant in T3. Overall, the original UTAUT tested in this research did not perform as well as Venkatesh et al. (2003)'s study which claim to have an R^2 of approximately 70 percent. This is despite replicating the whole original UTAUT by including moderators, as well as conducting in 3 different time periods from pre-implementation to sustained implementation, which is what Venkatesh et al. (2003) tested in their original UTAUT.

Table 5.5 Summary of applying UTAUT model

T 1 (Month 1: Pre-Implemetation)			**T2 (Month 2-3)**			**T3 (Month 4-5)**		
	Beta	**P Values**		**Beta**	**P Values**		**Beta**	**P Values**
EE -> BI	**0.110**	**0.007**	**EE -> BI**	**0.263**	**0.004**	EE -> BI	0.085	0.336
PE -> BI	**0.506**	**0.000**	PE -> BI	0.076	0.399	**PE -> BI**	**0.183**	**0.025**
SI -> BI	0.059	0.407	**SI -> BI**	**0.225**	**0.018**	**SI -> BI**	**0.318**	**0.001**
FC -> BI	0.062	0.157	FC -> BI	-0.063	0.359	**FC -> BI**	**0.339**	**0.000**
			FC -> Actual Use	**0.285**	**0.000**	**FC -> Actual Use**	**0.252**	**0.002**
			BI -> Actual Use	**0.346**	**0.000**	**BI -> Actual Use**	**0.402**	**0.000**
Age*EE -> BI	-0.043	0.243	Age*EE -> BI	0.076	0.646	Age*EE -> BI	0.105	0.363
Age*FC -> BI	-0.007	0.854	Age*FC -> BI	-0.090	0.261	Age*FC -> BI	-0.095	0.357
Age*PE -> BI	0.027	0.505	Age*PE -> BI	0.148	0.402	Age*PE -> BI	0.060	0.597
Age*SI-> BI	-0.006	0.892	Age*SI -> BI	-0.147	0.348	Age*SI -> BI	0.027	0.778
Gender*EE -> BI	0.057	0.154	Gender*EE -> BI	0.046	0.606	**Gender*EE -> BI**	**0.178**	**0.031**
Gender*PE -> BI	-0.065	0.116	Gender*PE -> BI	0.115	0.173	Gender*PE -> BI	-0.113	0.163
Gender*SI -> BI	-0.050	0.301	Gender*SI -> BI	-0.143	0.113	**Gender*SI -> BI**	**-0.228**	**0.028**
Experience*EE -> BI	-0.061	0.175	**Experience*EE -> BI**	**0.151**	**0.021**	Experience*EE -> BI	0.025	0.775
Experience*FC -> BI	0.039	0.379	Experience*FC -> BI	0.038	0.482	Experience*FC -> BI	-0.050	0.428
Experience*SI -> BI	**-0.100**	**0.044**	**Experience*SI -> BI**	**-0.257**	**0.002**	Experience*SI -> BI	0.030	0.777
	R^2	Adjusted R^2		R^2	Adjusted R^2		R^2	Adjusted R^2
BI	0.28	0.256	BI	0.311	0.25	BI	0.534	0.486
			Actual Use	0.202	0.194	Actual Use	0.335	0.328

5.4.3 Mediating effect of motivation to learn EHR

As recommended by Hair et al. (2016), when testing mediating effects, researchers should follow Preacher and Hayes (2008) approach and bootstrap the sampling distribution of the indirect effect. The reason why bootstrapping is used is because it makes no assumptions about the sampling distribution of the data, which is very suited for the PLS-SEM method employed in this research (Hair et al., 2016). Mediation analysis was conducted based on the procedure recommended by Hair et al. (2016). A summary of the procedure is shown in Figure 5.4. The first step conducted was to assess the significance of the direct effect of the UTAUT predictors with actual use of EHR without including the mediator variables in the PLS model.

Table 5.6 Significance Analysis of UTAUT direct effects without mediators at T1 (Pre-Implementation Stage)

	Standard Deviation	**T Statistics**	**P Values**
Performance Expectancy -> Behavioral Intention	0.043	0.830	0.386
Effort Expectancy -> Behavioral Intention	0.049	0.716	0.476
Facilitating Conditions -> Behavioral Intention	0.043	0.115	0.909
Social Influence -> Behavioral Intention	0.084	0.776	0.439

Table 5.7 Significance Analysis of UTAUT direct effects without mediators at T2 (Implementation Stage)

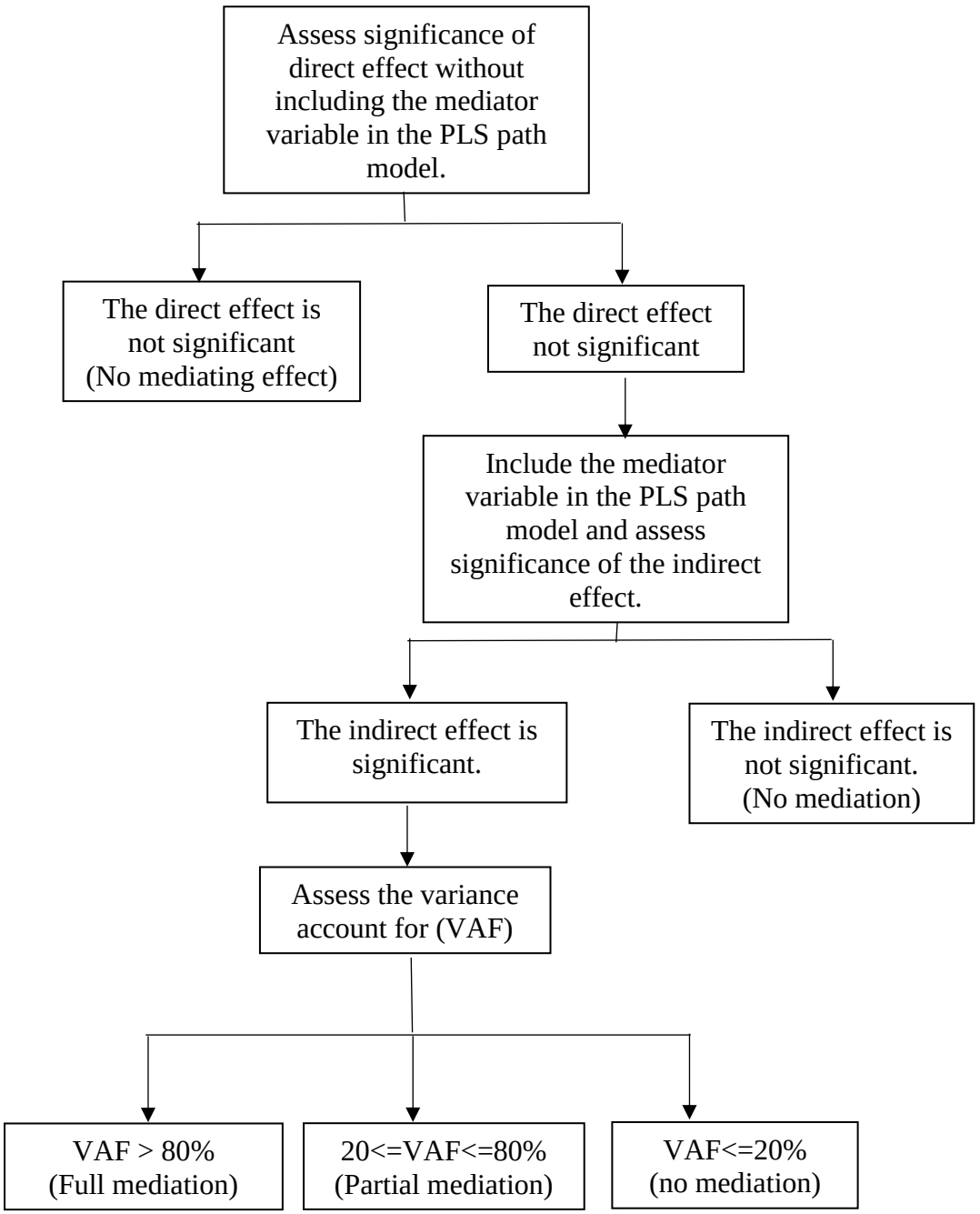
	Standard Deviation	**T Statistics**	**P Values**
Effort Expectancy -> Actual Use	0.086	0.613	0.541
Facilitating Conditions -> Actual Use	0.105	0.28	0.780
Performance Expectancy -> Actual Use	0.166	0.578	0.565
Social Influence -> Actual Use	0.092	0.169	0.866

Table 5.8 Significance Analysis of UTAUT direct effects without mediators at T3 (Sustained Implementation)

	Standard Deviation	**T Statistics**	**P Values**
Effort Expectancy -> Actual Use	0.113	0.912	0.362
Facilitating Conditions -> Actual Use	0.099	0.685	0.493
Performance Expectancy -> Actual Use	0.081	1.317	0.188
Social Influence -> Actual Use	0.13	0.661	0.509

As shown in Table 5.6, Table 5.6 and Table 5.7, the direct effects of UTAUT predictors on behavioural intention at T1 and actual use of EHR at both T2 and T3 are not significant. As a result, it can be concluded that motivation to learn EHR has no mediation effect on the UTAUT predictors and behavioural intention/actual use of EHR.

Figure 5.4 Mediator Analysis Procedure in PLS-SEM (Hair et al., 2016, pp. 224)



5.5 Summary of Chapter

This chapter provides the data analysis conducted in this dissertation. PLS-SEM was performed to test the longitudinal data from T1 to T3. The measurement model as well as the structural models were both examined. The significance values and R^2 values of the models were discussed and compared. In order to examine if the proposed model can outperform Venkatesh (2003)'s UTAUT, this study also applied PLS-SEM to test the original UTAUT model on the data collected. As shown from the results, the proposed model which included perceived goal attainment, perceived velocity, team learning behaviour and motivation to learn in this thesis performs much better than Venkatesh (2003)'s original UTAUT. The proposed model also better explains why healthcare professionals in Malaysia adopt and use EHR. Mediation tests were also conducted in this chapter but the result shows that motivation to learn does not mediates the relationships between the UTAUT predictors and behavioural intention and actual use of EHR.

CHAPTER 6 DISCUSSION OF RESULTS

6.1 Introduction

This chapter discusses the findings based on the data analysis conducted in the previous chapter. A discussion on how the results answered the research questions proposed in Chapter 1 will also be presented.

6.2 Discussions of Findings

6.2.1 Can UTAUT be extended to include goal attainment, perceived velocity and team learning behaviour to better predict healthcare professionals' motivation to learn, behavioural intention to adopt and accept EHR?

The results from this study shows that the research model applied in this study performs better than the original UTAUT, with high adjusted R^2 values of 0.545 and 0.540 in T1 for motivation to learn and for behavioural intentions to adopt EHR, and at T2 with adjusted R^2 values of 0.339 and 0.351 for actual use of EHR and motivation to learn, while at T3, the model has an adjusted R^2 values of 0.51 for motivation to learn EHR and 0.132 for actual use of EHR. Other than the actual use of EHR at month 4-5, the models strongly outperformed the original UTAUT, and these values are also much higher than the threshold suggested by Tan and Ooi (2008). This shows that by extending UTAUT to include motivation to learn EHR, team-learning behaviour, perceived attainment, and perceived velocity can better explain healthcare professionals' adoption and use of EHR.

The three variables proposed that extended UTAUT, namely perceived attainment, perceived velocity, and team learning behaviour, are all-important

predictors of EHR behavioural intention to use and acceptance at different stages of EHR implementations. During the pre-implementation stage, the result shows that perceived attainment, perceived velocity and team learning behaviour have a positive and significant relationship with behavioural intentions to use EHR, while perceived attainment also influences motivation to learn EHR. Perceived attainment is among the strongest predictors in the model based on its beta values. This result is consistent with Huang and Zhang (2011), which suggests that in the beginning of goal pursuit (i.e. learning and using EHR), healthcare professionals will be strongly influenced by whether they think the goal is achievable, or in other words "can I get there?" Although effort expectancy is slightly related to the factor as it measures how easy is it for a person to learn the IS, easy to learn does not translate fully into a user being eventually successful at using the system. Interestingly, after including the additional variables not found in the original UTAUT, the original UTAUT variables (e.g. effort expectancy, performance expectancy, and facilitating conditions) mostly performed well in predicting behavioural intention to use EHR in the pre-implementation stage.

These results in general are consistent with findings from most UTAUT studies, as well as UTAUT studies that were conducted for EHR (Venkatesh et al., 2011). There are however two slight differences to the results of UTAUT. First, social influence is found to have no significant relationship with behavioural intention in all 3 stages of EHR implementation. One possible explanation is that team learning behaviour, which unlike social influence that focuses on how people of importance view whether someone should or should not use the system, plays a

more dominant role as it solves team members learning and supporting each other in using the system. Thus, instead of being influenced by colleagues and line managers, a culture of colleagues and line managers working and learning together will bring more success to the adoption of EHR. This is consistent with Asian culture that places importance on group rather than individual achievement (Kim et al., 2001). This is supported by the fact that team learning behaviour continues to be a significant predictor at all three time periods of EHR implementation. Second, facilitating conditions which is proposed to have no significant influence or weak predictor on behavioural intention by Venkatesh et al. (2003), Venkatesh (2011) and Chong et al. (2015), is found to be a strong predictor of EHR behavioural intention to use. Therefore prior to starting to use the EHR system (i.e. pre-implementation), healthcare professionals need to be assured that there is organizational and technical support. This result is consistent with other healthcare related technologies adoption (Chong and Chan, 2012; Najaftorkaman et al., 2015).

Perceived velocity is also an important predictor of behavioural intention to use EHR, which in turn affects the actual use of EHR. As shown in the results, velocity is an important predictor during pre-implementation as well. This contradicts with suggestions from Huang and Zhang (2011) who found that velocity should only become important at a later stage instead of in the beginning. However, during pre-implementation as discussed in terms of motivation to learn EHR, healthcare professionals are more concerned with "can I get there" rather than "when will I get there", as velocity has no significant relationship with motivation to learn EHR. The results from this study though are interesting

as being similar to the suggestions from Huang and Zhang (2011), as the implementation of EHR progresses from T1 to T3, in the context of motivation to learn EHR, perceived attainment's effects start to reduce while perceived velocity increases its effects as implementation moves from T2 to T3. This shows that as users become more experienced in using EHR, their concern with whether they will learn how to use EHR will reduce. Instead, they now pay more focus to how quickly they can learn the full features of EHR and use the system well, hence, they are more motivated to learn EHR.

This study has found several important moderating effects of experience, gender and perceived velocity. The results show that facilitating conditions moderated during month 2-3 (T2) of EHR implementation, but the effect is no longer significant in month 4-5 (T3) of implementation. This is supported by Venkatesh et al. (2011) which stated that the fundamental mechanism underlying experience as a moderator is that as an individual gain in experience, problems that existed in the early stages will dissipate, thus rendering the effects into intention to be weaker over time. Therefore, over time, as users gain more experience, facilitating conditions no longer become a factor in determining their actual use.

In this study, genders moderate the effort expectancy of users during months 2-3 (T2) and months 4-5 (T3) of EHR implementation, as well as performance expectancy during month 2-3 (T2) only. This supports what is proposed by UTAUT and also supports Venkatesh and Morris (2000) findings where females are more likely to be influenced by ease of use of an IS compared to males.

Lastly, perceived velocity moderates performance expectancy of users in terms of their motivation to learn EHR. This shows that healthcare professionals will view EHR to be more useful when they are learning to use the system much faster.

6.2.2 Is there a significant relationship between motivation to learn EHR and EHR behavioural intention to adopt and accept EHR among Malaysian healthcare professionals?

In terms of the UTAUT variables, many are found to have no significant relationship with the actual use of EHR. Although as discussed earlier where UTAUT variables predict behavioural intentions to use EHR well, none of the factors were found to have a significant relationship with actual use of EHR. However, when introduced the motivation to learn EHR, predictors such as performance expectancy, social influence, and facilitating conditions show that they are important predictors at different time periods of EHR implementation. This suggests that UTAUT should be extended not only from the predictors as conducted by most studies (Venkatesh et al., 2016; Maruping et al., 2018), it is also useful to introduce new mediating or dependent variables to the UTAUT. In the context of this study, motivation to learn EHR is introduced to the extended UTAUT. Table 6.1 below presents an overview of the results of hypotheses tests for this study.

Table 6.1 Hypotheses results

Hypotheses	Results
H1a Performance Expectancy will have a significant and positive influence on behavioural intention to use EHR	**Supported**
H1b Performance Expectancy will have a significant and positive influence on motivation to learn how to use EHR, but the influence will decrease over time.	**Supported**
H1c Performance Expectancy will have a significant influence on actual use of EHR, but the influence will decrease over time	Not Supported
H2a Effort Expectancy will have a significant and positive influence on behavioural intention to use EHR	**Supported**
H2b Effort Expectancy will have a significant and positive influence on motivation to learn how to use EHR, but the influence will reduce over time	Not Supported
H2c Effort Expectancy will have a significant influence on actual use of EHR, but the influence will decrease over time	Not Supported
H3a Social influence will have a significant and positive influence on behavioural intention to use EHR	Not Supported
H3b Social influence will have a significant and positive influence on motivation to learn how to use EHR	**Partially Supported**
H3c Social influence will have a significant influence on actual use of , but the influence should increase over time	Not Supported
H4a Facilitating conditions will have a significant and positive influence on behavioural intention to use EHR	**Accepted**
H4b Facilitating conditions will have a significant and positive influence on motivation to learn how to use EHR	Not Supported
H4c Facilitating conditions will have a significant influence on actual use of , but the effect should reduce over time.	Not Supported
H5a Perceived goal attainment will have a significant and positive influence on behavioural intention to use EHR	**Supported**
H5b Perceived goal attainment will have a significant and positive influence on motivation to learn how to use EHR, but the influence will reduce over time.	**Supported**
H5c Perceived goal attainment will not have a significant influence on actual use of EHR	**Supported**
H6a Perceived velocity will have a significant and positive influence on behavioural intention to use EHR	**Supported**
H6b Perceived velocity will have a significant and positive influence on motivation to learn how to use EHR, and the influence should gradually increase over time	**Supported**
H6c Perceived velocity will have a significant and positive influence on actual use of EHR	Not Supported

H7a Team learning behaviour will have a positive and significant influence on behavioural intention to use EHR	**Supported**
H7b Team learning behaviour will have a positive and significant influence on motivation to learn how to use EHR	**Partially Supported**
H7c Team learning behaviour will have a positive and significant influence on actual use of EHR	Not Supported
H8a Motivations to Learn EHR will have a significant and positive influence on behavioural intention to use EHR	**Supported**
H8b Motivations to Learn EHR will have a significant and positive influence on the actual use of EHR	**Supported**
Hypotheses for moderating Effects	**Results**
H9a The effect of performance expectancy on motivation to learn to use EHRs will be moderated by gender	**Partially Supported**
H9b The effect of effort expectancy on motivation to learn to use EHRs will be moderated by gender	**Partially Supported**
H9c The effect of social influence on motivation to learn to use EHRs will be moderated by gender	Rejected
H10a The effect of performance expectancy on motivation to learn to use EHRs will be moderated by age	Rejected
H10b The effect of effort expectancy on motivation to learn to use EHRs will be moderated by age	Rejected
H10c The effect of social influence on motivation to learn to use EHRs will be moderated by age.	Rejected
H10d The effect of facilitating conditions on motivation to learn to use EHRs will be moderated by age	Rejected
H11a. The effect of effort expectancy on motivation to learn to use EHRs will be moderated by experience	Rejected
H11b. The effect of social influence on motivation to learn to use EHRs will be moderated by experience	Rejected
H11c. The effect of facilitating conditions on motivation to learn to use EHRs will be moderated by experience	**Partially Supported**
H12a The effect of effort expectancy on motivation to learn to use EHR will be moderated by perceived attainment	Rejected
H12b The effect of performance expectancy on motivation to learn to use EHR will be moderated by perceived attainment	Rejected
H13a The effect of effort expectancy on motivation to learn to use EHR will be moderated by perceived velocity	**Partially Supported**
H13b The effect of effort expectancy on motivation to learn to use EHR will be moderated by perceived velocity	Rejected
H14a Motivation to learn EHR mediates the relationships between the UTAUT variables and behavioural intention to use of EHR	Rejected

H14b Motivation to learn EHR mediates the relationships between the UTAUT variables and actual use of EHR	Rejected

6.3 Summary of Chapter

This chapter discussed the findings from this research. This chapter first presents the results derived from examining the conceptual model proposed in this thesis. The chapter presents whether each of the hypotheses presented in this thesis is accepted or rejected. Each of the research questions proposed in this thesis were discussed. In the next chapter, the implications, limitations, and future studies recommended will be presented.

CHAPTER 7 CONCLUSION, IMPLICATIONS, LIMITATIONS AND FUTURE STUDIES

7.1 Conclusion

This research examined the factors that influence the adoption of EHR by healthcare professionals in Malaysia. UTAUT was adapted and extended by including motivation to learn, perceived goal attainment, perceived velocity and team learning behaviour. The new model was tested in the context of EHR system adoption and use by healthcare professionals. This research conducted a longitudinal field study in a medical group of clinics that implemented an EHR system. This research found that although the original UTAUT did not perform well in explaining behavioural intention and use of EHR, by extending UTAUT to include perceived attainment, perceived velocity and team learning behaviour to explain motivation to learn EHR, the model could explain EHR behavioural acceptance and use much better. This research has significant contributions to two vital streams in which this study is rooted: HIT and technology adoption. The next sections discuss the theoretical and practical contributions of this research.

7.2 Theoretical implications

There are several important contributions for this research. Firstly, this research examined how well UTAUT can be applied to understand medical professionals' behavioural intention to accept and use EMR. There have been questions by scholars on UTAUT's generalizability. Previous studies have stated that although UTAUT is one of the most cited theories in the field of information systems, the theory has not been applied correctly leading to inconsistent results,

or the empirical testing of UTAUT is quite limited (Venkatesh et al., 2011; Venkatesh et al., 2016; Taiwo et al., 2013; Dwivedi et al., 2017). One of the key issues with existing UTAUT studies is that these studies only selectively pick on some UTAUT predictors (e.g. Wong et al., 2015; Blut et al., 2016) or they have ignored the moderators proposed by UTAUT (e.g. Hew et al., 2015; Slade et al., 2015), which is an important contribution of UTAUT. These issues have been confirmed by Venkatesh et al. (2016) recent synthesis and review of UTAUT studies. Context has always being recognized as an important boundary condition for the adoption of theories. However, theories only recently advocated taking a proactive approach in considering context in theory development (Venkatesh et al., 2011). Therefore, this study examines the utility of UTAUT by testing it in the context of EHR adoption behaviour and use by medical professionals in Malaysia, an Asian country. Our findings revealed that when applying UTAUT contextually of EHR, the original relationships between the predictors and adoption decisions proposed by UTAUT vary, just as when Venkatesh et al. (2011) applied the model to study electronic medical records. Theoretically, we have examined the boundary conditions of UTAUT, and found that in the context of different technologies and at different locations, UTAUT should be extended to better explain the adoption behaviours.

Secondly, as discussed above, given that the boundary conditions of UTAUT have been tested and the result shows that there is a need to extend the model to study EHR adoptions in Malaysia, this research proposed and tested a new UTAUT model. Previous studies have shown that at times, UTAUT needs to be extended by integrating with other theories or predictors to better explain the technologies studied. For example, Chong and Ngai (2013) extended UTAUT

with elaboration likelihood model (ELM) when studying travellers' decisions to adopt location-based social media for their travel planning. Zhou et al. (2010) similarly integrated UTAUT to explain mobile banking adoption. Venkatesh and his colleagues similarly extended his own original UTAUT by proposing the UTAUT2 when examining consumer related technologies (Venkatesh, et al, 2012). In this study, UTAUT is extended by integrating factors in goal pursuit theory such as perceived attainment and perceived velocity, as well as team learning's behaviour. As review of extant literature shows, this is the first UTAUT extended model that examined the roles of perceived attainment, perceived velocity and team learning behaviour in understanding what influences healthcare professionals' adoption and use decisions. As shown in the results discussed in the previous chapters, the extended UTAUT models explained behavioural intention and actual use of EHR much better than just applying the UTAUT model.

Thirdly, this study addresses Maruping et al. (2017)'s arguments that there are limitations to using behavioural intentions as a sole proximal determinant of IS adoption and use. In order to use an IS, this study proposed that users' motivations should play a key role. Previous studies on technology adoption have examined the roles of extrinsic and intrinsic motivations. Intrinsic motivations such as perceived enjoyment and satisfaction has been examined by researchers such as Zhou (2011), Chong (2013), Venkatesh et al. (2012), Lacka and Chong (2016). Extrinsic motivations such as performance expectancy, rewards in technology acceptance have also been examined by studies such as Lee et al. (2005), Teo et al. (1999) and Yoo et al (2012). Despite the extensive studies on motivations, there is almost no study that examines the motivation to

learn the technology. Logically, users will need to learn how to use an IS before using it. A factor closely resembling this is learning goal orientation (Yi and Hwang, 2003) as discussed in earlier sections. Therefore, this study has extended UTAUT as well as technology adoption studies by proposing and confirming the link between the motivation to learn the system and the eventual acceptance of the system.

Lastly, similar to Venkatesh et al. (2011) and Venkatesh and Davis (2000), this study collected longitudinal data, and tested the proposed model as well as the UTAUT model over three periods of time, namely pre-implementation of the EHR system during the first month, the 2-3 month, and the 4-5 month period. The findings show that the predictors do vary during the different time periods. This is important as scholars have argued previously that technology acceptance studies should conduct longitudinal studies (Benbasat and Barki, 2007; Venkatesh et al., 2016) in order to see if the predictors of IS adoption and usage will perform consistently over time. As shown in this study, variables in UTAUT as well as the extended UTAUT model proposed in this study vary in their effects over different implementation time periods. Therefore, for future technology adoption studies, it is important not only to consider cross-sectional samples, as the results and findings of such approaches may not provide a full picture of the entire technology diffusion process. Instead, future studies should consider collecting longitudinal data when testing IS adoption models. (Chong and Chan, 2012).

7.3 Practical Implications

This study informs practice in several ways. Firstly, this research proposed and tested a model that focused on EHR implementations in Malaysia. The topic on EHR has been gaining the attention of the government, scholarly community and healthcare industry. The medical industry has been identified as a key industry to the Malaysian government, and Malaysia's healthcare services have consistently been ranked as among the world's best. However, medical clinics and hospitals that are key components of the healthcare industry have not been quick adopters to IS technologies when compared to its neighbouring peers such as Singapore and Thailand– two countries that are among Malaysia's competitors for the medical tourism sector. Despite the importance of the EHR system which can ensure that hospitals and clinics operate more efficiently, the adoption of the system remains low. The medical group companies conducted in this study is among the largest group of private clinics in Malaysia, and yet until the recent two to three years, many of its clinics are still using a paper-based system in the operations. The importance of conducting research related to EHR is demonstrated by a recent call from Kohli and Tan (2016) which stated that IS researchers should pay more attention to EHR developments and investigate research to understand how EHR can transform healthcare performance.

Secondly, clinics and hospitals that are implementing EHR should note that motivation to learning EHR will lead to better actual use of the system in the early stage of EHR implementation. As such, healthcare professionals should be provided with the necessary facilities and training to motivate them to learn. As

shown in our findings, before implementing EHR, companies should let users know that the system will have good performance when compared to the previous approach (i.e. manual paper based system). Furthermore, during such early pre-implementation stages, employees' motivation to learn EHR will be influenced by social influence. Hence, the companies should ensure that important people in the company, or project champions, should encourage employees to learn EHR. Another important strategy companies should employ to increase the motivation to learn is to ensure and tell employees that the goal of learning and using EHR is highly attainable. In terms of ensuring that users are going to adopt the system, in the early stage of implementation, companies should provide good technical supports and infrastructure to employees who are going to adopt EHR. Employees should also be informed that their progress in learning to use EHR is quite fast to show that they can reach their learning goals quite quickly. The company should also ensure that there is a positive team-learning environment, where team members are encouraged to discuss and share their ideas and views on using the EHR system.

Thirdly, once companies have moved into using the system in the early stage, they should continue to ensure that employees are motivated to learn how to use EHR and to provide support when needed so that staff are encouraged and motivated to continue using the system. In designing the learning features of the system to users, the system can show the progress of learning (e.g. progress bar or task bar) to motivate users since perceived velocity is important to users. Employees should continue to be informed of the usefulness of the EHR system. The team learning environment should continue to be maintained in order to encouraged employees to use the EHR system.

Fourthly, after employees have continued to use the system over time and are getting used to the system, the company should note that employees now know that the goal of learning and using EHR is achievable, and the company should therefore emphasize to employees that they are learning to use the system at a fast rate, and they will be able to use the EHR system smoothly very soon. In designing the EHR systems, progress bar could be shown to users who are learning faster than others to further encourage these users. They will keep employees to continue to be motivated to learn how to use EHR system. At this stage, companies should also ensure that there is sufficient training and technical support (i.e. facilitating conditions), as employees will start to encounter more issues as they start to use the system more in their work. Companies should also ensure that important people such as senior managers continue to encourage employees and let them know that it is important to use the EHR system (i.e. social influence).

Lastly, gender is found to have moderating effects on performance expectancy, effort expectancy on the motivation to learn EHR systems. Therefore, when developing a training programme for the users, it could be worthwhile for companies to have slightly different programme for males and females. During this training, rather than having a one size fits all training programme, companies can highlight on the features (e.g. performance expectancy) or easiness to learn the system (e.g. effort expectancy) can be provided differently to the different gender group.

Table 7.1 below provides a summary of the practical recommendations to Malaysian clinics and hospitals that would like to implement EHR system.

Table 7.1 Summary of practical recommendations

Stage 1 – Pre-Implementation	***Stage 2*** – Short Term Effects	***Stage 3*** – Long Term Effects
▪ Users have not used the system, and hence their behavioral intention to use the system in heavily influenced by performance expectancy, effort expectancy, facilitating conditions and social influence. ▪ This is similar to previous hypotheses proposed by original UTAUT. ▪ However, in using a new technology, their motivation to learn the technology will influence behavioral intention. ▪ Attainment is important influence to motivation to learn. The belief that the goal of learning to use the EHR systems is attainable will influence the motivation. ▪ Team learning is important to behavioral intention to use the system.	▪ 1.5 month after using the system, users are still adapting to it. ▪ As they start using the EHR systems, they will explore with more features, and they are still influenced by whether how useful all these features are. ▪ At this stage, effort expectancy and social influence will influence actual use, which contradicts to UTAUT. ▪ As users start using the system, how fast they learn using the system compared to others now motivate their use. This means if they are behind others, they will spend more efforts. ▪ Team learning will influence actual use now that they are using the system.	▪ By now users are using the system and company should focus on whether the use is sustainable. ▪ This is the critical stage that will determine if technology will be diffused in the organization. ▪ Users who has more experience in using previous systems are now more likely to persist and use the system. ▪ Facilitating condition will no longer influence users' long term use. However, it will motivate them to learn more about the system. ▪ Team learning behavioral increases its significance. ▪ Attainment is no longer important. ▪ Velocity is still important and plays a more important role but now users who learn faster are more motivated as compared to stage 2. ▪ Social influence continues to be important.
Recommendations		
▪ Ensure that during workshop, examples of successful cases are being shared. ▪ Features of EHR systems should be clearly demonstrated to show how the system outperforms previous systems, or processes. ▪ Staffs should be informed that the system can be learnt, it is achievable. ▪ Team should work together. Encourage more team building efforts. ▪ Senior management or important people in the company should encourage and influence other	▪ The company should continue to offer support to users, especially those who are more experience in using the EHR systems. Those who are experience may explore the system more, and hence may be faced with more issues with using the system, and hence there is a need to have good supports to them. ▪ Users should continue to be encouraged that the goal is attainable. ▪ System can show the progress of learning (e.g. progress bar or task bar) to motivate users.	▪ Progress bar should show users who are learning faster than others. ▪ There should be mechanism to help users learn faster (e.g. incentives) ▪ More workshops to encourage team learning activities. ▪ Project champion should still be assigned.

employees to learn and use the system. ▪ Company can consider appointing project champions that influence others to use the system.	▪ Users should be informed of the usefulness of the EHR systems. The company can let employees know better the features of the systems and how they can be used to improve their job.	

7.4 Limitations and future studies

Despite the contributions of this study for both the theory and practice, there are several limitations. First, our model is based on data collected from doctors, paraprofessionals, and administrators. As such, when examining users' behaviour on EHR motivation to learn and actual use, we have grouped all three groups of healthcare professionals into one category. Instead, in order to obtain further insights on whether there is a difference among these healthcare workers, it would be useful to conduct separate studies with different data sets that compare doctors, paraprofessionals and administrators' motivation to learn and accept EHR. Unfortunately, sample size of this study is too small for the individual category of healthcare professionals to conduct a comparative study of different user group. Thus, future studies can consider testing the extended UTAUT model in this study by replicating the study on different user groups.

Second, this study collected samples only from clinics of a large medical group. Although working with the medical group offers a great opportunity for this study to examine adoption of EHR systems from pre-implementation to later stage of implementation via longitudinal study, future studies can replicate the research model in other healthcare organizations such as hospitals in Malaysia or other countries to further examine the model's generalizability. Opportunity

also exists for future researchers to conduct a cross country comparisons between data collected from Malaysia and other countries which have different cultural characteristics. For example, Venkatesh and Zhang (2010) conducted a cross country study between USA and China to test if there are differences in UTAUT's findings as a result of cultural differences. Another direction for future studies is to apply this theory to different types of HIT. This research was given the opportunity to work with Mediviron Group of Clinics to study their EHR implementation. However, in order to test the model's applicability to other technologies, it would be worthwhile for other researchers to examine the conceptual model proposed in this study to other technologies such as RFID, ERP and others.

Third, this study also extended UTAUT with factors from goal pursuit theory and team learning behaviour. However, it is possible that variables from other theories can be employed to this study. For example, this study did not examine factors related to privacy and security, which could influence EHR adoption. Theories such as Privacy Calculus Model for example, would be a good foundation for future researchers that want to examine the adoption of EHR from the privacy perspective.

Fourth, the unit of analysis in this study is based on individual respondents. Currently, most studies on healthcare technologies are based on either organizational level (e.g. Chong and Chan, 2012) or from individual level such as this thesis. However, there are scholars such a Venkatesh et al. (2016) and Jeyaraj et al. (2006) which suggest that researchers can consider using individual characteristics in organizational adoption studies to assess the characteristics of

individuals within organizations that facilitate IT adoption. Therefore, future scholars can consider applying some individual variables from this thesis such as goal attainment and perceived velocity when examining EHR adoption using organization as a unit of analysis. Such study can integrate these individual characteristics with organizational adoption study variables such as organization size, managerial training, strategic role of IS to name a few. With techniques such as multi-level structural equation modelling becoming more common, it is possible to examine these individual and organization variables in one research model.

Fifth, this study is only examining the adoption of EHR from the perspective of healthcare professionals. However, in order to EHR implementation to be successful, it is also important to consider if patients are willing to use the technology, or whether patients feel that EHR can lead to better performance (e.g. patient satisfaction) from the healthcare providers. This approach is similar to study conducted by Venkatesh et al. (2011) where besides examining the antecedents of EHR implementations from the perspective of healthcare professionals, the research also examines if EHR will lead to better healthcare service delivery. Examining the combinations of the antecedent of EHR behavioural intention and actual use together with healthcare performance outcomes in one conceptual model would further advance our understanding on HIT implementation and technology adoption theory.

Lastly, this study is conducted in Malaysia where there is a collectivist cultural environment. As such, the respondents may have a tendency to agree to the survey questionnaire regardless of the content of the questions, and this may

have slight chance of acquiescence bias in our data. Despite the limitations discussed, this study has provided compelling insights to help understand the adoption of EHR systems in Malaysian.

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Appendix 1

Full list of existing healthcare information systems adoption research

Authors	Theory used	Types of IS studied	Summary of study
Abdekhoda et al. (2014)	TAM	Healthcare Information Management	This study assessed the acceptance of Healthcare Information Management (HIM) by using TAM. A survey was distributed to collect data from 187 personnel who work in medical records departments of hospitals affiliated to Tehran University of Medical Sciences. The results confirmed that TAM is able to assess user acceptance of information technology in the context of HIM.
Aggelidis et al. (2009)	TAM	Healthcare Information Management	This study developed a modified TAM to example HIS adoption. The original TAM is extended to include some exogenous variables to examine HIS acceptance by 283 Greek hospital personnel. The results indicate that perceived usefulness, ease of use, social influence, attitude, facilitating conditions and self-efficacy significantly affect hospital personnel behavioral intention. Training has a strong indirect impact on behavioral intention through the mediators of facilitating condition and ease of use. Furthermore, the existence of significant positive effects between self-efficacy and social influence, perceived usefulness and anxiety, and facilitating conditions and social influence is also supported.

Alaiad and Zhou (2014)	UTAUT	Home Healthcare Robots	This study attempts to understand the determinants of home healthcare robots' adoption from an extended UTAUT model. The authors employed both qualitative and quantitative methods. The 108 participants were recruited from home healthcare agencies located in the U.S. The sample include both patients and healthcare professionals. The key findings of this paper show that usage intention of home healthcare robots is influenced by social influence, performance expectancy, trust, privacy concerns, ethical concerns and facilitating conditions. Among them, social influence is the strongest predictor. Monitoring vital signs and facilitating communication with family and medication reminders are the most preferable tasks and applications for robots.
Alaiad and Zhou (2015)	UTAUT	Wireless Sensor Network-smart home healthcare systems	This paper examines patients' intention to use Wireless Sensor Network- smart home healthcare systems based on UTAUT model. 83 patients participated in this survey study. Nevertheless, this paper did not apply the full UTAUT and only applied performance expectancy, effort expectancy and social influence. The model is also extended using cost and life quality expectancy. The results confirmed the proposed model.
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 is used as a predictor to user satisfaction and ERP implementation success. 175 respondents' survey data was 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.
Archer and Cocosila (2011)	TAM/UTAUT/ TAM2/TRA	Electronic Health Record	In this paper, the authors examined the adoption of EHR based on Canadian medical practitioners' perceptions. This paper integrated TAM/TAM2, UTAUT and TRA. Based on 185 users, the authors found that behavioral intention of adopt EHR is influenced by performance expectancy, perceived overall risk, and effort expectancy of users. This research found that job relevant will influence performance expectancy, while a user's personal innovativeness will influence effort expectancy. Other factors related to risks are also examined such as perceived performance risk, perceived psychological risk, and perceived legal and privacy risk. The paper adopted partial variables from the models proposed.
Basak et al. (2015)	TAM	Personal Digital Assistant (PDA)	The authors examined behavioral intention to use personal digital assistant (PDA) technology among physicians in Turkey. An extended Technology Acceptance Model (TAM) was applied. TAM was extended with subjective norm, personal innovativeness, computer self-efficacy and perceived enjoyment. A structural equation-modeling was applied to test the data collected from 339 physicians in Turkey to confirm the model.

Bhattacherjee and Hikmet (2008)	TAM	IT	This study examines the role of organizational support in motivating organizational members' usage of information technology (IT). Two organizational support factors (i.e. infrastructure support and technical support) were link to IT usage perceptions based on TAM. A survey data was collected from healthcare administrators. The results suggest that organizational support plays a critical role in shaping user perceptions toward IT and their subsequent IT usage. TAM was extended on this research by incorporating organizational support variables.
Byomire and Maiga (2015)	TAM/UTAUT	Mobile technology	This research focused on the adoption of mobile phones for maternal healthcare in Uganda. Using a survey, the study identified factors for successful Adoption of Mobile Phones in Maternal Healthcare. Maternal healthcare professionals were the respondents for this study. The results indicate 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.

Chang et al. (2015)	TAM	web-based appointment system	Chang et al. (2015) examine the e current status of web-based appointment system (WAS) implementation in Taiwan, and examines 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.
Chau and Hu (2001)	TAM/TPB	Telemedicine Technology	Chau and Hu (2001) examined telemedicine's acceptance based on 400 physicians working in tertiary hospitals in HK. They developed several conceptual replication of models for comparison studies. The models under investigation are the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and a decomposed TPB model. Their final result suggests an integrated TAM/TPB is able to help understand physician's telemedicine technology adoption.
Chau and Hu (2002)	TAM/TPB	Telemedicine Technology	Chau and Hu (2001) in this paper, proposed a paper that extended TAM by examining individual and technological contexts. The additional variables included compatibility, peer influence, and perceived technology control. Data were collected from physicians in HK and their result confirmed the proposed model.

Chen et al. (2007)	UTAUT	RFID	Chen et al. (2007) examined factors that contribute to the adoption of Radio Frequency Identification (RFID) technologies by the medical team in emergency room. The model examined was based on UTAUT such as performance expectancy, effort expectancy, social influence and facilitating conditions. However, the relationships proposed to influence behavioral intention and use behavior are different from the original UTAUT. Furthermore, moderators in UTAUT are also missing from their model.
Chen et al. (2014)	TAM	Generontech nology	The main aim of Chen an Chan (2014) is to examined a senior technology acceptance model (STAM) aimed at understanding the acceptance of gerontechnology by elderly Hong Kongners. The proposed STAM extended TAM by adding age-related health and ability characteristics of older people (e.g. health condition, cognitive ability, social relationships, attitude to life and satisfaction etc.). The model was empirically tested using a cross-sectional questionnaire survey with a sample of 1012 seniors aged 55 and over in Hong Kong. .
Chen et al. (2013)	TAM	hospital e-appointment system	In this paper, the authors extends TAM) by incorporating relationship quality as a mediator towards continuance intention of hospital e-appointment system. Data was collected from 334 Taiwanese. The model proposed is relatively simple, but relationship quality is measured using satisfaction and trust. The limitation of the model is that by combing trust and satisfaction under one

			variable (i.e. relationship quality), the result does not show which of the factors play a more important role in influencing continuance intention. Furthermore, the authors did not discuss why didn't they apply ECM which is more appropriate to study continuance intention behavior.
Cho et al. (2014)	TAM	Smartphone health app	This paper examines the effects of cognitive and contingent factors on the adoption of smartphone health apps. TAM was extended by including subjective norm, health consciousness, health information orientation, and Internet health information use efficacy significantly. The proposed model was confirmed from data collected from 422 American college students.
Chow et al. (2012)	TAM	Second Life for healthcare education	This paper examines if second life can be used to enhance healthcare education. Specifically, the paper examines the use of second life for learning rapid sequence intubation (RSI), which is a frequently used method of acute airway management in healthcare settings. The intention of learners to use the system was explored based on the TAM, with the computer self-efficacy construct as an external variable. Two hundred and six nursing students participated in the study and the model was confirmed from data collected from them.

Cimperman et al. (2016)	TAM/UTAUT	Telehealth	The objective of this paper is to develop and empirically test a model for predicting the factors affecting older users' acceptance of Home Telehealth Services (HTS). Data was collected from 400 participants aged 50 years and above from both rural and urban environments in Slovenia. The predictors affecting acceptance behavior are Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Perceived Security.
Cocosila and Archer (2012)	TAM/UTAUT	Electronic Health Record	The authors examined the adoption of electronic EHR from the perspective of consumers. A cross-sectional survey conducted among Canadian consumers found that perceptions of usefulness and personal information technology innovativeness are the main factors that encourage people to use EHR, while information-seeking factors are comparatively less important.
Cocosila and Archer (2014)	TAM	Electronic Health Record	This research examines consumer perceptions of EHR and validate it by conducting a comparative study between consumers who report having a chronic illness and those who report being well. TAM's perceived usefulness is used to predict users' behavioral intention, and factors such as information seeking, computer anxiety, personal innovativeness and security perception are found to predict perceived usefulness. The data examined was collected from 800 individuals, the authors also found little difference in perceptions of electronic PHRs between chronically ill and well individuals.

Daim et al. (2013)	TAM/UTAUT	Wireless service prototype of diabetes and obese patients	This paper studied the predictors of the adoption of health information technologies through the use of a case study of a wireless service prototype developed for patients with diabetes and obesity. TAM was used as the basis of theoretical framework. Results showed that the usefulness of an e-health service was affected by the quality of service, its compatibility with users' lifestyle, the quality of support, the quality of information presented in the service, usage time, image, accessibility, and ease-of-use characteristics of the service.
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 turned are moderated by gender. Facilitating conditions are left out of their study without providing strong discussion. A sample of 82 users were collected to test their research model.
Escobar-Rodríguez et al. (2012)	TAM	E-prescription system	This paper study health care personnel (physicians and nurses)'s intentions to use e-prescriptions and automated medication-management systems. The theoretical grounding for the paper is TAM, and the model is extended based on training, perceived risks and perceived compatibility. They also added a variable known as perceived usefulness to enhance control systems which in a way duplicated the perceived usefulness variable proposed in the model (e.g.

			two perceived usefulness variables).
Escobar-Rodríguez et al. (2014)	TAM/DOI	General IT in healthcare	This paper investigates the diffusion of IT's innovations in hospitals by applying TAM and DOI and compare the differences between early and late adopter. Through field study, the study compared 108 early adopters and 101 late adopters. The research confirms the model proposed by the researchers.
Fadel and Brown (2010)	UTAUT + Coping theory	General IS in healthcare	In the paper, the authors integrated UTAUT with coping theory to understand users' post-adoptive reactions to IS. This paper examined how adoption-related IS perceptions influence individual-level post-adoptive IS appraisal. UTAUT factors are proposed to have an influence on primary appraisal behavior (i.e. Benign/Positive, Harm, Threat and Challenge) and Second Appraisal (Control). Survey data was collected from IS users at a university health center. Their results indicate that performance and effort expectancies surrounding use of the IS strongly influence primary IS appraisal (judgments of what is at stake as a result of the IS). On the other hand, facilitating conditions influence secondary IS appraisal (judgments of what can be done in response to the IS). The paper however, excluded the moderators in the UTAUT.

Fensli et al. (2008)	TAM/UTAUT	Wearable biomedical sensors	Rune et al. (2008) examined the factors that influence patients respond to wearable biomedical sensors based on TAM and UTAUT. The authors developed a Sensor Acceptance Model using two questionnaires developed for measuring the patients' perceived acceptance of wearable sensors. Their proposed model is tested with 11 patients using a newly developed wearable ECG sensor, and with 25 patients in a reference group using a traditional "Holter Recorder". The main contribution of the paper is the development of a sensor acceptance index which included variables related to users' reactions towards the sensor such as skin reactions, anxiety from wearing the device etc.
Gagnon et al. (2014)	TAM/TAM extend/Psychosocial Model/Integrated Model	Electronic Health Record	In this paper, the authors study the determinants of physician acceptance of EHR based on general practitioners and specialists in Quebec, Canada. Questionnaire was sent to physician members of the Quebec Medical Association. The authors proposed and tested four theoretical models TAM, Extended TAM, Psychosocial Model, and Integrated Model. A total of 157 questionnaires were collected, and the four models all have a 44% and 55% of the explained variance. Among the four models, the Integrated model performed the best and showed that perceived ease of use, professional norm, social norm, and demonstrability of the results are the strongest predictors of physicians' intention to use the EHR. Age, gender, previous experience moderated the determinants and intention. .

Gajanayake et al. (2013)	TAM	Electronic Health Record	In this conference paper, the authors tested the role of perceived usefulness and attitude on the intention to use electronic health records by future healthcare professionals. The authors applied using polynomial regression with response surface analysis to examine the potential non-linear relationships in the model. Their findings reveal that the relationships between perceived usefulness and attitude are more complex than predicted in prior research, e.g. not a linear relationship, thus opening up the opportunity for research to apply different techniques to test TAM related studies.
Gao et al. (2015)	UTAUT2/PMT/ Privacy Calculus Theory	Wearable device	Gao et al. (2015) investigated the factors that can predict consumer's intention to adopt wearable technology in healthcare. An integrated acceptance model was developed based on UTAUT2 and protection motivation theory (PMT), and privacy calculus theory. The model was tested with 462 users via survey. Their findings indicate that healthcare wearable technology is affected by factors from technology, health, and privacy perspectives. Specially, 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 authors, however, 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	Based on a survey of 500 respondents, this paper tested an technology acceptance model based on the Protection Motivation Theory. Their result shows that threat appraisal and coping appraisal factors influence adoption intention through attitude. Furthermore, gender and age play different moderating roles with threat appraisal and coping appraisal factors
Guo et al (2012)	TAM	Mobile Health Service	Based on TAM, this paper tested the antecedents of perceived usefulness. Social norm and outcome quality both are found to influence users' perceived usefulness of mobile health service. Data was collected from a field survey of 492 subjects. The key findings of this paper include: (1) while perceived ease of use significantly influences perceived usefulness, the role of perceived ease of use and perceived usefulness on adoption intention are not significant. (2) Outcome quality positively influences perceived usefulness; (3) Social norm influence both adoption intention and perceived usefulness as well.
Guo et al. (2013)	TAM + Dual Factor model	Mobile Health Service	Based on the Dual Factor Model, the authors investigate the enablers and the inhibitors of elderly users' adoption intention on mobile health service. Two characteristics related to elderly users are proposed (i.e. technology anxiety and dispositional resistance to change). These characteristics are integrated to TAM. Data was collected from 204 elderly Chinese users. The main findings

			revealed that resistance to change influences perceived usefulness. However, it does not influence perceived ease of use and adoption intention. The authors also found that technology anxiety is negatively associated with perceived ease of use, but it positively influences resistance to change. Lastly, dispositional resistance to change has a negative influence on perceived ease of use, but it influences positively with resistance to change.
Hanson et al. (2011)	UTAUT	Social media in healthcare.	The paper examines the factors that determine the acceptance of social media use among healthcare educators. Data was collected from 503 Certified Health Education Specialists. The model of the study is based on UTAUT. Their study confirms UTAUT's applicability in studying social media use among healthcare educators. Additional variables included in this study include employer's approval of social media use in workplace.
Holden et al. (2012a)	TAM	Barcode medication administration	This study uses a cross-sectional survey of 83 registered nurses at an academic pediatric hospital that implemented barcode medication administration. Besides TAM variables such as perceived ease of use and perceived usefulness of the system, the study included variables such as social influence, training and technical support. Their result suggest that adoption intention is strongly predicted by perceived ease of use, perceived social influence and perceived usefulness.

Holden et al. (2012b)	TAM	Barcode medication administration	This study aims to understand pharmacy workers' perceptions and acceptance of a recent implemented barcode medication administration system. Survey data was collected from pharmacists and pharmacy technicians at an American hospital. TAM was extended by social influence, as well as splitting perceived usefulness into two types of usefulness - usefulness for the user's performance, and performance for patient care. The study also examined both adoption intention and user satisfactions. Their result confirmed their proposed model.
Hsiao and Tang (2015)	TAM	Mobile Health Service	Hsiao and Tang (2015) developed and tested a model to understand users' mobile healthcare technology acceptance. Their model includes variables derived from sociological, technological, and individual attributes. 338 data were collected from users to examine predictors such as perceived ubiquity, personal health knowledge, and perceived need for healthcare in their model. Their empirical results confirm the role of perceived ubiquity, personal health knowledge, and perceived need for healthcare in predicting the attitude of users, which lead to eventual adoption intention decision.
Hsiao and Chen (2016)	TAM/Activity theory	Computerized clinical practice guidelines	This study examines factors that influence physicians' intention to adopt computerized clinical practice guideline. TAM and Activity theory are employed in the authors' study. Data was collected from physicians from hospitals that have implemented the system. 238 data were collected to test the

			conceptual model. Their result suggests that users' attitudes toward using computerized clinical practice guidelines is influenced by organizational support, perceived usefulness and social influence.
Hsiao et al. (2013)	TAM	Decision Support Systems	The authors studied factors that affect the acceptance of decision support system for managing patient pains. Data was collected from nurse anesthetists in a hospital. 101 survey data were used to test the proposed model. Their result showed that perceived information quality, computer self-efficacy and organizational structure significantly influence nurse anesthetists' perceived usefulness of the system. Information quality on the other hand, influence nurse anesthetists' perceptions of ease of use of the system. Both perceived ease of use and perceived usefulness on the other hand, influence nurse anesthetist's decision to accept the system.
Hsieh (2016)	UTAUT/Status Quo Bias theory	Cloud Computing	Extending Hsieh (2015), this study also examines cloud services in healthcare, but from the patient's perspective in terms of their intention to use and resist the system. Data was collected from Taiwanese users to examine their proposed model. Hsieh's findings revealed that patients' resistance to use cloud service is related to suck costs, inertia, perceived value, transition costs, and uncertainty. However, UTAUT factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions are

			shown to have positive and direct influence on patients' intention to use the cloud services. The model however, neglected the moderators proposed in UTAUT.
Hsu et al. (2013)	UTAUT	Healthcare Information Management	This study examines users' intention to adopt healthcare information management system. UTAUT is used as the theoretical lens of the paper. The authors however, extended UTAUT by including perceived security and information security literacy of users into the model. Their results show that perceived security has a mediating effect between information security literacy and user adoption. UTAUT variables are confirmed to be important predictors although UTAUT is not fully employed as the model misses the moderating effects of age, gender and experience.
Hung et al. (2012)	TAM/UTAUT/ TPB	Healthcare Information Management	Hung et al. (2012) examined physicians' intention to use a healthcare information management system known as Medline. This is a system used in Taiwanese hospitals. The authors presented a model that contain variables from UTAUT, TAM and TPB, as well as a user's personal innovativeness. 224 physicians participated in the survey study. The authors found that physician's intention to use Medline is influenced by attitude, subjective norm, and perceived behavior control. These factors on the other hand, are influenced by perceived usefulness and perceived ease of use, interpersonal influence, personal innovativeness in IT and self-efficacy.

Ifinedo (2012)	UTAUT	Healthcare Information Management	The authors extended UTAUT with compatibility to understand healthcare professionals' intention and use behavior of healthcare management. Data was collected from 227 healthcare professionals in Canada. Besides performance expectancy, the other UTAUT variables and compatibility are found to have an influence on adoption intention and use behavior. The model however, neglected the moderators proposed in the original UTAUT.
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 based model in this research. The authors found that 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 results
Jackson et al. (2010)	UTAUT	PDA	The researchers applied DOI and UTAUT to examine healthcare workers' (i.e. resident and physicians) intentions to adopt PDA. 222 data were collected to test the proposed model. Variables such as perceived usefulness, perceived ease of use, perceived behavioral control, subjective norm and users' innovativeness are studied. Despite the results confirming the model proposed, the issue with the study is that there is

			no real UTAUT or DOI variables being used, despite claiming to do so in the paper. The model used is actually TAM as opposed to what is claimed by the authors.
Jaradat et al. (2013)	TAM	mobile healthcare information systems	The authors of the paper extended TAM in order to examine factors that affect users' intention to employ mobile healthcare information systems. The variables used to extend TAM include trust, security and privacy, social influence and compatibility. 366 users from Jordan participated in this study. Results showed that perceived ease of use is the most important predictor of users' behavioral intention to use mobile healthcare information systems, while other factors are also confirmed in the study.
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 extended to include compatibility, self-efficacy, and technical support and training. 94 Android smartphone users used the app for two weeks, followed by completing a survey designed to determine the factors that influence their intention to use the app. The results revealed compatibility, perceived usefulness, and perceived ease of use influence the behavioral intention to use the mobile obesity-management app. Technical support and training are also found to significantly affected the perceived ease of

			use. However, self-efficacy's impact on perceived usefulness and perceived ease of use were not supported in this study. As the study is based on users who have used the app for 2 weeks, a more appropriate theory would be the Expectations Confirmation Model (ECM), although this is not mentioned in the paper.
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. 123 users participated in the study, which built its model based on UTAUT, TAM and TPB. The factors examined by the paper 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 the paper is that all three models are not fully adopted, and there is little explanation why are some variables selected or omitted.
Ketikidis et al. (2012)	TAM	Healthcare IT	In this paper, the researchers extended TAM in order to assess the acceptance of HIT systems by health professionals. 133 healthcare users participated in the study. Unlike most studies, this study applied ANOVA to examine differences in TAM-related variables between nurses and medical doctors. However, there is no significant differences found in the result. The paper also further

			examines the predictors of HIT usage intentions. Their findings revealed that perceived ease of use, job relevance and subjective norms directly predicted HIT usage intentions. Perceived usefulness, however, was found to be not significant predictor in this research.
Kijsanayotin et al. (2009)	UTAUT	Healthcare IT	This paper examines UTAUT to understand factors that influence health IT adoption in Thailand's community health centers. Data is collected from users from 1607 centres. UTAUT is extended in this paper by including IT knowledge. Experience and Voluntariness is used as predictors instead of moderators. The potential issue in this paper is that UTAUT has been examined to study organizational adoption decision (i.e. community health centres). As such, the model and data where the unit of analysis is individual may not accurately address the research questions posted in this paper. Nevertheless, the results show that Health IT acceptance is influenced by performance expectancy, effort expectancy, social influence and voluntariness. On the other hand, actual use of Health IT use is influenced by the user's previous IT experiences, intention to use the system, and facilitating conditions.

Kim and Park (2012)	TAM/TPB	Healthcare IT	This paper extended TAM to predict consumers' behavioral intention in adopting HIT. TAM is integrated with the Health Belief Model and TPN. Respondents are 728 members recruited from three online health portals in South Korea. The findings show that that perceived threat, perceived usefulness, and perceived ease of use significantly affected health consumers' attitude and behavioral intention. On the other hand, users' health status, health belief and concerns, subjective norm, HIT characteristics, and HIT self-efficacy is found to have a strong indirect impact on attitude and behavioral intention through the mediators of perceived threat, perceived usefulness, and perceived ease of use.
Kim et al. (2016)	UTAUT/TAM	Electronic Health Record	Kim et al. (2016) examine the factors that influence users' intentions to utilize a mobile electronic health records system. The authors use both online survey as well as log file data to capture actual use. Data was collected from 449 healthcare professionals in a university hospital for seven months. Based on the actual usage log analyses, it is found that both the doctors and nurses used the menus to view the inpatient lists, alerts, and patients' clinical data with high frequency. Users' intentions to use the electronic health record system is influenced by performance expectancy and attitude.

Klein (2007)	TAM	Patient-Physician Portals	In this paper, the authors empirically investigate patients' behavioral intentions to use electronic communications functions and also accessing their individual medical information through a web-based patient–physician portal. Data was collected from 294 patients to examine a conceptual factor that contains individual factors such as computer self-efficacy and personal innovativeness, as well as variables based on TAM. The findings revealed that usefulness and innovativeness have a positive direct effect on users' adoption intention on both functions (i.e. communications and information access).
Kohnke et al. (2014)	UTAUT	Telemedicine Technology	Based on UTAUT, this study examines the predictors of patients, clinicians, and agency personnel's' behavioral intention to adopt Telehealth equipment. Survey data was collected by 126 participants. The model included 3 types of moderators which are participant type, self-efficacy, anxiety and attitude. Results supported the proposed model.
Kowitlawakul (2011)	TAM	Telemedicine Technology	This study determine the factors that predict nurses' intention to use the telemedicine technology. The study is based on TAM and tested the data from 117 participants from two healthcare organizations. Their results show that perceived usefulness is the most influential factor that influences nurses' intention to use the telemedicine technology. Overall the results support the proposed model.

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, which is a system designed to interact directly with consumers. Consumers can now track their health status through the system, as well as obtaining some diagnosis information. The authors developed their model based on Theory of Reasoned Action, TAM, and UTAUT. Data was collected from 165 respondents. The findings found 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.
Kummer et al. (2013)	TAM2	sensor based medication support system.	The aim of the paper is to understand the attitudes and intentions of usage of professional nurses toward sensor-based medication systems. The paper is based on an adjusted extended technology acceptance model (TAM2). Through the use of a scenario of a sensor-based medication support system, 579 professional ward nurses participated in the study. Data were collected using an online questionnaire and explored using hierarchical regression analysis. The results show that perceived usefulness, image, demonstrability, qualitative and quantitative overload and personal innovativeness were found to have a significant impact on intention to use. Qualitative and quantitative overload also found to have a significant negative effect on personal innovativeness. The variables studied are also moderated by age.

Kuo et al. (2013)	TAM/Technology readiness index	Electronic Health Record	This paper examines nurses' personality traits with regards to technology readiness toward EHR acceptance. The Data was collected from 665 Taiwanese users. Among the personality traits of the technology readiness, the results support the notion that nurses are optimistic, innovative, secure but they are also not comfortable about technology. The four personality traits were also proven to have a significant impact on the perceived ease of use of EHR, but not perceived usefulness. Perceived usefulness of EHR also influence the optimism trait. The results also confirmed the relationships between the perceived of ease of use, usefulness, and behavioral intention in TAM.
Lai et al. (2015)	TAM	Mobile registration system	The modified technology acceptance model (MTAM) was applied in this study on the use of mobile clinic registration system in Taiwan. This model theorizes that perceived ease of use and perceived usefulness of the technology influence users' attitudes toward technology use. The model was tested using data collected from 501 patients in a Taiwanese medical center. Using path analysis, results showed that TAM is a valid model in investigating the factors influencing users' attitudes of using the mobile registration system.
Liang et al. (2003)	TAM	Personal digital assistant	Authors of this paper present an extended technology acceptance model (TAM) to predict personal digital assistants (PDAs) usage among healthcare professionals. This extended

			model incorporates three major determinants of PDA usage: perceived usefulness, perceived ease of use, while also including three external variables: job relevance, compatibility and support. 173 survey responses from a healthcare professional were collected and analyzed using PLS. The results provided strong support for the proposed model.
Lin et al. (2012)	TAM	Electronic medical record	Physicians' adoption of electronic medical record is explored using the theoretical foundation of the TAM model in this study. In this research model, perceived usefulness is viewed as the enabler of technology acceptance, whereas perceived threat and perceived inequity are seen as barriers. Survey data collected from 115 physicians from 6 hospitals was analyzed using SEM to verify the research model. The results provided overall support for the model.
Lishan et al (2009)	TAM revised into Female Focused Acceptance Model	Female-focused healthcare applications	In this study, the difference in perception and acceptance levels of Female-focused Healthcare Applications (FHA) among female healthcare and non-healthcare workers were explored. The study draws on a revised version of the TAM model, called female-focused acceptance model (FAM). Regression analyses were performed on data collected from 1071 females in Singapore (241 were healthcare workers and 830 were non-healthcare workers). Results demonstrated that FAM is a viable model for detecting social variables that may influence female acceptance.

Looije et al. (2010)	UTAUT	Persuasive robotic assistant	This paper presents an experiment that compares a text-based interface with a virtual and physical character providing health assistance for older adults to evaluate user acceptance of persuasive robotic assistants. Several subjective and behavioral measures were used to measure to what extent participants of the experiment perceived the assistants as empathic and trustworthy actors, and to what extent the personal assistant were treated as a social actor. Questions on acceptance (one of several items) in the questionnaires used in this experiment were derived from the UTAUT model. Results show that participants found the virtual and physical character more empathic and trustworthy than the text-based assistant. They also expressed more conversational behavior with the characters. However, more conscientious people liked the text interface better. Further, older adults responded more negatively to the characters that lacked social behaviors, than to the text interface.
Lu et al. (2012)	TAM/ISSM	Hospital information system	Authors of this study proposed an evaluation model that draws on both the TAM and ISSM models in order to investigate the factors influencing nurses' acceptance of hospital information systems. This proposed model comprises six constructs based on TAM and ISSM: system quality, information quality, service quality, perceived usefulness, perceived ease of use, and system acceptance. Data collected from 277 nursing staff working in a hospital in Taiwan were analyzed. SEM results confirmed that the proposed model explains nurse

			acceptance of hospital information systems.
Maarop et al. (2011)	TAM	Teleconsultation	This study is focused on the acceptance of teleconsultation technology among healthcare providers of public hospitals in Malaysia and compares the level of user acceptance between emergency and non-emergency setting. The TAM model was adopted for this study. Results of this study showed that the levels acceptance of teleconsultation technology in both emergency and non-emergency settings are high, with no significant difference in levels of acceptance. However, in terms of the validity of the TAM model in this context, results showed that the acceptance of teleconsultation is only moderately correlated with perceived usefulness of the technology, and not significant to perceived ease of use.
McDowell et al. (2008)	TAM	Point-of-care information system	In this study, a research model was proposed to examine the role of nurses' perceptions of ease of use, usefulness, and documentation accuracy on perceived quality benefits of information systems. This model was developed based on the TAM model, where the independent variables are made up of two TAM constructs: perceived ease of use and perceived usefulness, alongside the nurse's perception of documentation accuracy. The dependent variable in this model is the

			perceived quality benefits. The proposed model was tested and confirmed using data collected from 121 hospital nursing staff's survey responses.
Melas et al. (2011)	TAM	Clinical information system	This study focuses on the intention to use clinical information systems using an extended TAM model that introduced physician's specialty as a moderator, and medical staff's ICT knowledge and ICT feature demands as external variables. The model was tested against a sample of 604 medical staff working in 14 hospitals in Greece. Results demonstrated the model's ability to predict the intention to use clinical information systems.
Monthuy-Blanc et al. (2013)	TAM	Telemental health	This research paper adopts the TAM model to investigate the role of mental health service providers' attitudes and perceptions of telemental health on their intention to use this technology. To test the TAM model, data were collected from 205 mental health service providers who were working on 32 First Nations reserves in Canada. Results from confirmatory factor analysis and SEM of the data confirmed the validity and reliability of the model in this study.

Moores (2012)	TAM	Clinical management system	This study developed and tested an integrated acceptance model that incorporates components of the TAM model and compares the role of attitude, use, and compatibility as measures of IT acceptance. Perceived usefulness is defined in terms of information quality (accuracy, content, format and timeliness), whereas perceived ease of use is defined in terms of enabling factors for users to use the system (computing support and user efficacy). The model was tested and applied to the adoption of a clinical management system for hospital workers. Upon PLS analysis, results showed strong support for proposed the model.
Nisha et al. (2016)	UTAUT	m-Health services	This paper examines the role of service quality and knowledge as factors influencing future use intentions of m-Health services in Bangladesh. 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 play an important role in overall perceptions of m-Health services.

Or et al. (2011)	UTAUT	Web-based interactive self-management technology	This study employs the UTAUT theory to investigate the factors that influence patients' acceptance and perceived effective use of a web-based interactive self-management technology for home care patients. Patients' acceptance was measure by behavioral intention in this study. Data were collected from 101 participants and latent variable modelling with item parceling was used to test the research model. Results confirmed the model and showed that perceived usefulness, perceived ease of use, subjective norm, and healthcare knowledge predict most of the variance in patients' acceptance and use of the technology.
Ortega Egea et al. (2011)	TAM	Electronic healthcare record	Authors of this paper extended the original TAM model to include trust and risk-related factors (physicians' perceptions of institutional trust, perceived risk, and information integrity) to investigate physicians' usage intentions of electronic healthcare records (EHCR). The model was tested with a SEM of the data collected from a sample of 254 physicians in Spain. Results indicated that in the 'core' model as covered in the original TAM, attitude was the only direct determinant of physicians' intention to use EHCR systems whereas the 'extended' research model further supported the important role of institutional trust in facilitating physicians' acceptance of EHCR systems.

Pai and Huang (2011)	TAM + IS success model	Healthcare information system	This paper adopts a conceptual model that integrates the system, service, and information qualities covered in the Information System Success Model together with the three dimensions of perceived usefulness, perceived ease of use, and intension to use as established in TAM2. This model was used to study the intention to use a healthcare information system and was tested with data gathered from district hospital nurses, head directors, and other related personnel in Taiwan. SEM analysis showed that information, service and system quality influence user's intention through the mediating constructs, perceived usefulness and perceived ease-of-use.
Smith et al. (2014)	TAM	Mobile computerized provider order entry	This study proposes a new model to explore the user acceptance of mobile computerized provider order entry (MCPOE) deployment. The proposed model uses core TAM constructs, while also examining the roles of psychological ownership, perceived threat, perceived risk, and resistance to change. The model was tested empirically wait a group of physician users of a new MCPOE system recently deployed at a North American hospital. Results show that resistance to change had a significant effect on perceived ownership and perceived ownership had a significant effect on perceived usefulness. Also, perceived ownership has a strong and significant mediation effect on resistance behavior and perceived usefulness.

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. The overall behavioral intention model explained 24% of the variance.
Swaid (2010)	TAM/UTAUT/Flow thoery/SERVQUAL model	Health website	This study focusses on quality attributes of health websites in consideration of the African American perception. The research incorporates theories of TAM, UTAUT, flow theory and the SERVQUAL model. Focus group and two-round factor analysis were conducted, and results show that health website quality is defined as a function of dimensions such as aesthetic design, website usability, information quality, information architecture, responsiveness, trust, identity, appropriateness to culture, and learnability.
Tsai (2014)	TAM/Social capital theory; social cognitive theory	Telehealth	Authors of this paper developed a comprehensive behavioral model that integrates social capital theory, social cognitive theory and TAM to study the relationships among social capital factors, technological factors and system self-efficacy in telehealth. The proposed model was tested and validated using data collected from 365 respondents in Taiwan, followed by a SEM analysis. Findings showed that the proposed integrative psychosocial-technological model fitted well.

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 use 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 model with performance expectancy, effort expectancy, and facilitating conditions being significant predictors of usage intention.
Whetstone and Goldsmith (2009)	TAM	Personal health records	In this study, the factors influencing consumers' intention to create and use personal health records (PHRs) are examined. The TAM model was adopted in this research. Findings from online questionnaires distributed to 542 US college students showed that being innovative with healthcare, confidence in privacy and security, and perceived usefulness were factors that positively relate with intent to create PHRs. However, gender, age, presence of a chronic illness, and awareness of PHRs were not found to be associated.

Wills et al. (2008)	UTAUT	Electronic medical record	Authors of this study conducted an evaluation of the acceptance of EMR among registered nurses, certified nurse practitioners and physician assistants. The study used the UTAUT model, and an analysis using partial least square (PLS) was done to estimate the variance. Results validates the use of UTAUT as a feasible assessment of health care professionals' acceptance of EMRs. Further, the results indicate that social influence is a significant determinant of intention and use.
Wong et al. (2014)	TAM	Internet	In this study, the authors investigate the predictors of Internet use for health information among Chinese older adults. TAM model was adopted to study the behavioral intention to search for health information using the Internet of 98 Chinese older adults. Main findings of the study showed that perceived ease of use and attitudes significantly predicted behavioral intention of Internet use.
Wright and Marvel (2012)	TAM/UTAUT/ ECM	Electronic Health Record	This paper's focus is on the effects of antecedents of technology adoption on physician satisfaction with EHR technology and the continued usage of such systems. An integrated model that merges technology adoption and computer user satisfaction models was tested using survey data collected from 453 physicians regarding their satisfaction and EHR use experience. SEM results show that effort expectancy (ease of use) has the most significant effect on physician satisfaction and the continued use of EHR systems.

Wu et al. (2011)	TAM/TPB	Mobile healthcare	This study proposed a framework that integrates TAM and TPB to explain the adoption behavior of mobile healthcare of healthcare professionals. Perceived service availability (PSA) and personal innovativeness in IT (PIIT) were integrated with TAM and TPB models in this proposed framework. Results from an empirical examination of the proposed model validated the influential role of these important variables and showed high predictive power for adoption intention.