UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Gordon Institute of Business Science
University of Pretoria

Predicting clinicians' intentions towards the electronic health record (EHR): an extended UTAUT model

Robyn Johnson

28120664

A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

11 March 2020

ABSTRACT

The Electronic Health Record (EHR) has the potential to promote understanding or awareness of healthcare knowledge among patients and healthcare providers to facilitate collaboration between various key stakeholders to improve the quality of healthcare. The technology is also expected to provide global health communities with benefits, from improved health outcomes, reduced medical errors, and a reduction in healthcare expenditure. These benefits will not be realised unless the key stakeholders and consumers of the technology are willing to accept, adopt, and use the EHR. The purpose of this study is to identify crucial factors influencing clinicians' adoption of the EHR in South Africa's healthcare system by expanding the Unified Theory of Acceptance and Use of Technology (UTAUT) model to include the additional constructs Resistance to Change and Attitude Towards Organisational Change. A cross-sectional online questionnaire was used to gather data from 168 clinicians employed at various private and public healthcare facilities across South Africa. Performance expectancy and facilitating conditions were found to have a statistically significant positive impact on clinicians' behavioural intention, whereas effort expectancy and social influence had no similar result. Resistance to change had a statistically significant negative influence on behavioural intention, and a negative attitude towards organisational change positively influenced resistance to change. The findings of this study can be used by government bodies, the private sector and technology vendors to better understand clinicians' perceptions of the EHR in order to guide policy and effect implementation strategies accordingly.

KEYWORDS

Health information technology; Electronic health record; Unified theory of acceptance and use of technology; Resistance to change; eHealth.

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

---------- ----------

Signed ***Date***

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

AeH	Accountable eHealth Records
AIDS	Acquired Immune Deficiency Syndrome
ATC	Attitude Towards Organisational Change
BI	Behavioural Intention
CAS	Change Attitude Scale
CDSS	Clinical Decision Support Systems
CSF	Critical Success Factor
CPOE	Computerised Physician Order Entry
EE	Effort Expectancy
EHR	Electronic Health Record
FC	Facilitating Conditions
GDP	Gross Domestic Product
HIS	Health Information Systems
HIT	Health Information Technology
HIV	Human Immunodeficiency Virus
IS	Information Systems
IT	Information Technology
JCM	Job Compatibility Model
PE	Performance Expectancy
RC	Resistance to Change
SI	Social Influence
UTAUT	Unified Theory of Adoption and Use of Technology

CHAPTER 1: INTRODUCTION TO THE RESEARCH PROBLEM

1.1 BACKGROUND: THE IMPORTANCE OF HEALTH INFORMATION TECHNOLOGY (HIT) IN HEALTHCARE

This study focuses on the importance of health information technology (HIT) in healthcare. The overall health of a population forms the basis of the economic development and performance of a country. However, inequities in healthcare provision and rising healthcare costs within and between countries remain a significant area of concern (Mengesha & Garfield, 2019). As a group, the emerging economies - Brazil, Russia, India, China, and South Africa (BRICS) - now account for 43% of the global populace and contribute to the bulk of global economic expansion (Jakovljevic et al., 2019). However, rapid, uncontrolled urbanisation and wage increases are the driving force behind the growing demand for improved access to healthcare in these regions, leading to a rise in unwelcome healthcare expenditure (Lewis, 2015).

Over the last decade, the total aggregate global healthcare expenditure in Gross Domestic Product (GDP) has been forecasted to reach US$8 trillion by 2020, with an expected year-on-year increase of 10% in emerging markets (Deloitte, 2018). As a result, emerging countries continue to suffer from insufficient healthcare financing, which, inadvertently, bears implications on access to quality healthcare and the overall health outcomes of its citizens (Krech, Kickbusch, Franz & Wells, 2018; World Health Organization, 2015). Furthermore, the compounding effects of an aging populace and rising burden of lifestyle diseases, such as heart disease, diabetes mellitus, hypertension, and obesity, on healthcare expenditure have been widely investigated and can no longer be ignored (Ahlan & Ahmad, 2014).

The enormous pressures on healthcare systems in emerging economies has generated a need to rethink the entire healthcare delivery model and develop viable alternative solutions. In this compelling macroeconomic case, digital health technology has attracted much recent attention from impact investors, who aim to finance innovative solutions that will improve health over the long term (Krech et al., 2018).

The emergence of technological innovation has become a salient practice in providing opportunities to resolve the apparent supply-demand gaps in the delivery of healthcare services to underserved communities (Ahlan & Ahmad, 2014; Ayanso, Herath, & O'Brien 2015). Health organisations and policymakers have inadvertently realised the importance

of investing in information technologies and its potential for enhancing the quality of healthcare service delivery worldwide (Bawack & Kamdjoug, 2018). One such technology is Health Information Technology (HIT), an electronic system used to track, retain, regulate, and transfer health sensitive data. Furthermore, HIT is known to better facilitate clinicians' decision-making process through the retrieval of health information when treating patients (Harried, Claybaugh, & Dai, 2019). HIT, simplified as the application of information technology (IT) in healthcare, can take the form of a broad spectrum of services such as mobile health (mHealth), telemedicine, the Electronic Health Record system, Clinical Decision Support System (CDSS), and medical data management (Adenuga, Iahad, & Miskon, 2017; Ahlan & Ahmad, 2014; Wu, Kao, & Sambamurthy, 2016).

There is a growing consciousness in recognising the advantages HIT has to offer in improving access to quality healthcare, reducing healthcare operating costs, and standardising healthcare delivery through the enhancement of medical practice (Adenuga et al., 2017). One of the most progressive tools using HIT for managing health information and improving healthcare delivery is the Electronic Health Record (EHR) (Sadoughi, Khodaveisi, & Ahmadi, 2019). Despite the proven benefits of the EHR, adoption, and under-utilisation remain a massive challenge for developing regions, mainly in Sub-Saharan Africa. Furthermore, many developed and developing regions continue to utilise traditional medical practices, such as paper-based systems, as the preferred means of healthcare provision (Bawack & Kamdjoug, 2018).

Hossain, Quaresma, and Rahman (2019) stated that the drawbacks of paper-based systems hinder patient continuity and the delivery of excellent healthcare service. Bawack and Kamdjoug (2018) reiterate that the disadvantages of traditional paper-based systems include the extensive utilisation of information technologies that could solve ambiguity, time-consumption, and health record duplication. This paper is based on a type of HIT - the EHR system.

1.1.1 THE HEALTHCARE ENVIRONMENT IN SOUTH AFRICA AND EHR ADOPTION

South Africa is regarded as the most unequal country in the world. Moreover, the emerging country has had to contend with a history of civil and political unrest, contributing largely to the disparities in healthcare across geographical areas (Marten et al., 2014). As a result, information technologies, such as telemedicine, are ineffectually valued (Scott &

Mars, 2015). Despite the constitutional obligation to the right to access safe and affordable healthcare, the health landscape remains largely fragmented between two parallel systems: the efficiently run, well-resourced private system and the poorly resourced, underperforming public system (Ramjee, Abraham, Kaplan, Taylor, & Vieyra, 2013; Winchester & King, 2018).

Demographics on South Africa show that the estimated population stands at 58 million (Stats SA, 2019). About 43% of the total population resides in remote areas with a doctor to patient ratio of 9.1:10,000 (Scott & Mars, 2015; World Health Organization, 2019). Approximately 13.3% of the General Government Expenditure (GGE) is utilised as total domestic health expenditure. However, given this investment, neighbouring countries that devote less of their GGE to health, such as Botswana (9.2%), have better health outcomes (Naledi, Barron & Schneider, 2011; World Health Organization, 2019).

Poor health outcomes can be attributed to a high number of maternal deaths (138 deaths per 100,000 live births in 2015), the high mortality rate for children under the age of five (37 to 40 deaths per 1,000 live births in 2019) and the dual burden of HIV/AIDS and tuberculosis (TB) (Bramford, McKerrow, Barron, & Aung, 2018; World Health Organization, 2015; World Health Organisation 2019). Universal Health Coverage (UHC) has been pledged by the South African government to provide efficient, equitable healthcare, and a key critical component of its success depends on an advanced EHR program (Katurura & Cilliers, 2018; Marten et al., 2014).

The main objective of the EHR is to mitigate these problems by reducing its impact on the local health sector (Bawack & Kamdjoug, 2018). Also, adoption of the EHR will better facilitate clinicians' decision-making process when treating patients through the access of health information, reduction in medical errors, preventing redundant diagnostic tests, and improving patient outcomes (Agha, 2014; Hossain, Quaresma, & Rahman, 2019). Despite the challenges emerging countries have previously and currently face, the use of limited resources to implement new digital health technologies has been a common trend. However, acceptance of the EHR in developing economies remains low (Ahlan & Ahmad, 2014).

The issue of technology adoption is also prevalent in developed regions. This is supported by Barrett (2018), who highlighted the prevalence of low EHR adoption in the United States (U.S.). According to the author, in 2009, the U.S. federal government introduced the American Recovery and Reinvestment Act (ARRA), which mandated that all

healthcare facilities implement the EHR programme by the year 2015 in an attempt to shift the healthcare sector into the digital age. Healthcare facilities would be assessed through the Medicare and Medicaid EHR Incentive Program (Meaningful Use), in aid of improving adoption rates through incentives (Brenner et al., 2016). It was found that the Meaningful Use criteria were difficult to achieve, and facilities who were non-compliant were to be penalised up to a 1% reduction in medical reimbursements (Barrett, 2018). One of the consequences of the government taking such an approach is the ongoing EHR resistance (Barrett, 2018).

1.1.2 INTENTION TOWARDS AND ADOPTION OF THE ELECTRONIC HEALTH RECORD

There are various stakeholders within the healthcare community who utilise digital health technology. Physicians were identified to be the critical deciding stakeholders in utilising electronic health platforms due to their ability to influence technology use within the healthcare community (Ayanso et al., 2015). A general observation by Hossain et al. (2019) was that higher optimism was reported in patients than in healthcare practitioners towards the adoption of electronic health technologies. The adoption of IT in healthcare involves the process of gathering patient records from various sources into a common digital storage platform (Ayanso et al., 2015). This process has been slowly integrated into the practice of healthcare in a step-wise manner with the expectation that clinicians would adopt the innovation over time to render better health care and improve patient outcomes (Ayanso et al., 2015).

Despite the great potential HIT systems have on mitigating the burden on the health system, clinicians' negative attitudes are a worrying sign that has the potential to restrict future technology adoption and implementation in healthcare institutions (Hossain et al., 2019). Hossain et al. (2019) assert the perceived threat associated with the technology is the product of clinicians' negative outlook toward the EHR system. Very few studies have researched the barriers to technology adoption in developing countries (Bawack & Kamdjoug, 2018). With the possibility of the nationalisation of South African healthcare (the National Health Insurance) imminent and a global shift towards a technologically dominated era, determining the factors which influence technology adoption and implementation in healthcare, especially utilising technology adoption frameworks, is imperative.

1.2 Research Problem

The research problem concerns the intentions of clinicians toward health information technology (EHR) adoption. Low technology adoption rates amongst medical professionals and underutilised facilities have been reported following a number of IT endeavors across the African continent (Mengesha & Garfield, 2019). Some clinicians' negative attitudes towards technology could be explained by their perceptions of technology interference with the patient-doctor relationship and current workflows (Hossain et al., 2019). A recent study by Hossain et al. (2019) found that some clinicians negatively perceived the use of technology as a time-consuming process.

The need for clinicians' co-operation in the implementation of digital innovation in healthcare necessitates this study. The dramatic changes in technological developments in healthcare, as well as the challenges health systems face across continents demand increased participation from key influential stakeholders.

Current research has explored the use of recognised theoretical frameworks and technology acceptance models to better explain the underutilisation phenomena of HIT amongst clinicians in developed and developing countries, as this concept is not well understood (Adenuga et al., 2017; Mengesha & Garfield, 2019). Knowledge of the impact of context-specific factors and reinforcement factors, such as incentives, on adopters' perception and intentions towards HIT in a developing setting, is lacking (Adenuga et al., 2017). In addition, resistance to change is described as a critical antecedent in determining clinicians' behavioural intention toward technology adoption; and negatively influences the relationship between behavioural intention and technology usage (Hossain et al., 2019; Shahbaz, Gao, Zhai, Shahzad, & Hu, 2019). Evidence supporting the impact of resistance to change as an antecedent of behavioural intention towards technology use in healthcare is lacking (Hossain et al., 2019). To address this research need, this study is aimed at obtaining an understanding of the factors influencing clinicians' behaviour towards HIT use and adoption in South Africa.

1.3 Research Purpose

This study is located in the field of technology adoption in health services. The first objective of this study is to obtain further insight into how access to healthcare can be improved through the adoption of EHR systems. The second objective is to identify the

factors that play a crucial role in EHR adoption. A third objective is to address the gap in literature regarding the role of resistance to change in EHR adoption. Without efforts geared towards improving healthcare in a country, it would be challenging to enhance the population health status and the overall economy (Mengesha & Garfield, 2019).

The cognisance of performing research in this field of study is increasing. Correspondingly, the growing trend of clinicians' reluctance to adopt new technology to improve patient care has also been the focus of information management research. This research aims to examine the factors influencing clinicians' intentions towards the adoption and use of the EHR using a well-renowned technology acceptance model, the Unified Theory of Acceptance and Use of Technology (UTAUT). The UTAUT encompasses psychological, social, behavioural, institutional, and technological-related factors to further explain physicians' intentions towards technology and will form the basis of this research (Hossain et al., 2019; Venkatesh, Morris, Davis, & Davis, 2003).

The literature proposes the UTAUT model as most efficient for this type of study (Venkatesh, Thong, & Xu, 2016). Researchers have attempted to extend the current UTAUT to challenge the existing model. However, Venkatesh et al. (2016) cautions against this and encourages researchers to have a paradigm shift towards model extensions and adopt a contextualisation approach to make more meaningful contributions to the framework (Venkatesh et al., 2016).

Furthermore, Venkatesh et al. (2016) made mention of the lack of research on the impact of technology use on individual outcomes, for example, job satisfaction, organisational commitment, and work performance. A study by Shahbaz et al. (2019) explains the role of resistance to change in the failure of IT acceptance in healthcare. In understanding the causes of clinician resistance, healthcare institutions will be able to improve EHR acceptance amongst employees.

Therefore, the following is the overarching research question that this study aims to answer:

What are the key determinants of the adoption and use of the EHR in the South African context?

1.4 Significance of Research for Business and Theory

1.4.1 Academic Justification and Business Rationale

This research aims to contribute to the theoretical knowledge of how user perceptions will affect the adoption and implementation of IT in healthcare practice. It further aims to establish which of the UTAUT model parameters, apart from performance expectancy, effort expectancy, social influence, and facilitating conditions are the most influential antecedents of clinicians' behavioural intention towards EHR systems in an emerging market. There is a seemingly positive relationship between the above parameters and the behavioural intention of clinicians to adopt the EHR, which substantially contributes to the successful implementation and use of the programme.

In a case report performed at the Ohio State University Wexner Medical Center (OSUWMC), the authors Rizer, Kaufman, Sieck, Hefner and McAlearney (2015), provide an example of the successful implementation of the EHR in a large academic medical facility. The authors summarised the top lessons learned from the case highlighting the need for agility on the part of the change management team. Furthermore, successful EHR implementation is possible in a dynamic healthcare environment with a diverse mix of specialist healthcare providers with differing practice styles (Rizer, Kaufman, Sieck, Hefner & McAlearney, 2015).

The healthcare system in South Africa faces a host of dynamic challenges. Investing in HIT is a necessary intervention to reduce rising transactional costs, improve human resource shortages, and standardise healthcare (Cline & Luiz, 2013). In understanding the various organisational barriers to HIT use and uptake, healthcare institutions and policymakers would be better equipped to develop technological innovations that are more appropriate or tailored towards healthcare contexts.

Furthermore, expertise on the barriers that hinder EHR adoption may offer useful data to policymakers during the development of protocols that will direct successful EHR implementation in a diverse emerging market (Hossain et al., 2019). The findings may also guide medical council bodies in improving the support of clinicians through various strategies such as training and development programmes, improvement of technical efficiency through reskilling programmes, and investing in the education and training of young medical students in EHR and other HIT.

Moreover, with the push towards the decentralisation of healthcare, the South African government could be better facilitated in terms of understanding the concerns of clinicians, which could guide the solving of pertinent organisational problems in existing healthcare facilities - such as improving infrastructure development. Therefore, the purpose of this study is to determine whether the adoption climate among South African clinicians is sufficient for widespread EHR adoption and use as exemplified in developed countries (Rizer et al., 2015).

1.5 Research Scope

The participants for this research were drawn from the healthcare industry in South Africa. It is believed that participants (clinicians) in the study may have had some degree of contact with an EHR system in their practicing careers. The participants in this industry, who operate in both public and private healthcare systems, were easily accessible to the researcher. Insights drawn from this research could be useful and applied to other developing settings with similar economies to South Africa.

1.6 Outline of the study

The remainder of this report is structured as follows. Chapter 2 presents the theoretical foundation (literature review). This is followed by Chapter 3, which presents the research questions, hypotheses, and the conceptual framework. Further, Chapter 4 details the research methodology, while Chapter 5 outlines the data analysis results. In addition, Chapter 6 is a discussion of the results and is followed by Chapter 7, which presents the conclusions and recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 THE INCREASING COMPLEXITY OF MODERN MEDICAL PRACTICE

The modern-day healthcare sector faces a host of different challenges – financial, strategic, digital, transformative, and human resources. Modern healthcare systems are also highly costly and complex (Tanwar, Parekh, & Evans, 2020). A recent trend in literature has seen the healthcare system and its functions being characterised in terms of complexity theory. While it is widely acknowledged that the definitions of complexity across literature are ambiguous, what remains consistent is that tasks or systems, such as healthcare systems, that range from "complicated" to "intractable" to "not simple," are complex (Kannampallil, Schauer, Cohen, & Patel, 2011, p. 943).

Kannampallil, Schauer, Cohen, and Patel (2011) describe how complexity can be understood by considering the interrelatedness of the small, functional components that exist within a system. The authors refer to this notion as functional decomposition. Functional decomposition is defined as a detailed interpretation of work in relation to its external context, its functional components, and the rules governing the web of interrelationships between the elements of a complex system (Kannampallil et al., 2011). As the operability of modern health care is distributed amongst its various actors (health care providers), patients and artefacts (health information technology, the paper-based system, medical equipment), the existence of these various components fit the characteristics of functional decomposition and therefore, complexity (Kannampallil et al., 2011).

The interplay between social (actors) and technical (artefacts) factors in complex hospital environments is critical when considering the implementation and adoption strategies of HIT, such as the EHR sharing system (Tanwar et al., 2020). Tanwar, Parekh, and Evans (2020) assert that the complexity of the healthcare market against the backdrop of complex hospital settings and increasing patient demands can be improved by the introduction of "medical record management… and blockchain technology" (p.1).

In the greater scheme of healthcare contexts, three types of complexities exist disease complexity, comorbidity complexity, and coordination complexity; the undesirable effects of which can be alleviated by EHRs (Wani & Malhotra, 2018). However, Mishuris and Linder (2013) cautioned that in the advent of Industry 4.0, HITs, such as the EHR system,

will only further complicate the lives of clinicians who already operate in complex, highly demanding hospital settings.

Chen, Lin, and Wu (2020) propose that the implementation and adoption of HIT, whether simple or not, involving big data fields are imperative. However, the low adoption rates in the healthcare industry have been attributed to the degree of complexity and the amount of effort required to operate EHRs (Chen, Lin, & Wu, 2020).

2.2 The Importance Of Healthcare Innovation

This sub-section presents the importance of healthcare innovation and comprises of adoption of HIT systems, and drivers of EHR adoption.

2.2.1 ADOPTION OF HEALTH INFORMATION TECHNOLOGY (HIT) SYSTEMS

HIT is broadly known as a “healthcare planning system” (Pai & Huang, 2011, p.651) that can support healthcare operations at three major levels: practical, tactical, and strategic (Sebetci, 2018). More specifically, HIT, such as EHRs, refers to a store of patient details in an electronic format that can be safely stored, analysed and exchanged (Hossain et al., 2019; Kruse & Beane, 2018).

Over the years, the myriad of benefits of IT, together with the unprecedented increase of the ageing population, has left government and policymakers with the challenge of advocating for digital inclusivity in society (Macedo, 2017). In such instances, HIT systems play an important role in assisting in both social and economic shifts (Macedo, 2017). The overall objective of HIT systems is to improve the quality of healthcare service delivery, health-provider performance, and overall public health (Kruse & Beane, 2018; Sebetci, 2018).

Bawack and Kamdjoug (2018) suggest that to maximise the benefits of HIT and efficiently deliver real-time data to the central server for the recollection of information, services such as EHRs and CDSS would need to be utilised extensively. The CDSS is closely related to EHRs as it provides healthcare providers with decision-making support (Hossain et al., 2019). Overall, the integration of HIT “through the creation of massive big data platforms…may ease therapeutic processes, since all parties involved would be better informed” (Heart, Ben-Assuli, & Shabtai, 2017, p. 21).

The Health Information Technology for Economic and Clinical Health (HITECH) Act was introduced by the U.S. federal government in 2009, in aid of accelerating the meaningful adoption and implementation of EHR systems across various healthcare settings (Heart et al., 2017; Kruse & Beane, 2018; Yen, McAlearney, Sieck, Hefner, & Huerta, 2017). The purpose of the Act was a cost-cutting exercise in the backdrop of rising healthcare expenditure due to an ageing populace. According to Agha (2014), the implementation of HIT was projected to reduce healthcare spend up to $142-$371 billion per year.

Since the implementation of the HITECH Act, the adoption rates of EHRs have shown exponential growth (Kruse & Beane, 2018). A critical overview of literature by Heart et al., (2017) supports this argument by reporting that until 2009, EHR adoption rates of 25% soared to 59% in the year 2016, following the implementation of the Act (p. 21). The adoption rates of EHRs have similarly increased worldwide. In contrast, Agha (2014) studied the impact of HIT adoption on the performance of therapeutic outcomes and quality of service utilising Medicare claims data from 1998 to 2005. The author concluded that from an economic value perspective, early investment into HIT is not associated with cost reductions and improved patient outcomes; therefore, explaining low adoption rates during this period (Agha, 2014).

Over the years, several studies have committed to exploring the relationship between HIT use and overall health outcomes, including an examination of the associated administrative costs and efficiencies of HIT implementation (Kruse & Beane, 2018). The central research enquiry of Kruse and Beane (2018) is whether patients have earned a commensurate improvement in healthcare quality and a decline in medical errors since HIT was introduced.

Heart, Ben-Assuli, and Shabtai (2017) stated that clinicians, in general, agree with the narrative of EHRs improving overall medical outcomes and, ultimately, patient safety. However, clinicians who do not adopt the HIT express concerns associated with the loss of daily productivity and the high initial implementation costs of the system. Mishuris and Linder (2013) conclude that despite its complexity, the EHR system will enable clinicians to perform optimally for their patients. With the uncertainties and complexities evident in modern healthcare, will healthcare professionals welcome added complexity while remaining focussed on delivering patient care of increasing quality and efficiency?

2.2.2 DRIVERS OF ELECTRONIC HEALTH RECORD (EHR) ADOPTION

This sub-section presents the drivers of EHR adoption. The benefits of the EHR and the reasons as to why healthcare needs an EHR are discussed. This includes a discussion on the EHR drivers, such as cost-effectiveness, access to health information, and improvements in productivity. Lastly, the disadvantages and barriers to EHR adoption are discussed.

2.2.2.1 BENEFITS OF THE EHR: WHY HEALTHCARE NEEDS AN EHR?

Innovation in healthcare is often seen as a means to facilitate socioeconomic prosperity. However, Tall, Hurd, and Glifford (2015) argue that due to the recency of HIT, there is a paucity of theoretical evidence related to the impact of technology like EHRs. Despite the sparse evidence in the literature to promote the influence of health information exchange (HIE) in improving overall healthcare delivery and cost-effectiveness, it maintains its superior potential in the healthcare industry (Sadoughi, Nasiri, & Ahmadi, 2018). It is critical, before the implementation of EHR systems, that healthcare practices should demonstrate an understanding of both the benefits and disadvantages these systems would potentially have on their healthcare facilities or practice (Holroyd-Leduc, Lorenzetti, Straus, Skyes, & Quan, 2011). This section will provide a further understanding of the potential benefits of EHR systems and optimistically, a clearer picture of what the relevant stakeholders are to expect from this technology in the near future.

2.2.2.1.1 COST-EFFECTIVENESS

It is widely believed that although the implementation of HIT systems may pose an additional cost to healthcare systems, the broad adoption of EHRs has shown the potential to ultimately reduce overall healthcare costs (Hossain et al., 2019). HIT systems have further assisted hospital management and administrative boards in cost-reduction (Adenuga et al., 2017). Dranove, Forman, Goldfarb, and Greenstein (2012) studied the dynamic association between EHR adoption and total operational costs of hospitals across multiple U.S. healthcare facilities from the years 1996 to 2009. The authors claimed that as the EHR automates the process of data collection, the reporting of patients' diagnostic information, medical test results, care provided and treatment rendered, and then linking this information to health insurance and medical billing; the technology will

potentially reduce costs by improving the accuracy of patient data collection (Dranove, Forman, Goldfarb, & Greenstein, 2012).

In Sebetci's (2019) assessment of health information systems (HIS), the EHR system is able to reduce healthcare costs through the following mechanisms: improving clinician efficiency and quality of service delivery, reduction in data communication costs among hospitals and medical professionals, reducing human errors through the support of decision-making services or prevention of data loss and patient record duplication. The cost-saving ability of EMRs is supported by one of the most frequently referenced EMR cost analyses by Hillestad et al. (2005). The author and team extrapolated the possible total net savings of adoption costs from peer-reviewed literature and reported on evidence of the mean value of the potential health care savings through EMR adoption. The potential areas of saving were identified as a reduction in adverse drug reactions, diagnostic imaging, laboratory testing, nursing time, and reduced hospital stay. The authors went further to conclude that if virtually every hospital in the U.S. improved the adoption rates of the EMR, this would produce a potential net cost savings of up to $77.4 billion after fifteen years, however, health care system changes should be in alignment (Hillestad et al., 2005).

2.2.2.1.2 HEALTH INFORMATION

EHR systems act as depositories and managers of valuable health sensitive information of patients (Adenuga et al., 2017). Hossain et al. (2019) state that IT systems are to improve the exchange of health information and preserve a Nationwide Health Information Network (NHIN), which seeks to promote a secure and functional network for medical data. For example, consider the actions of a clinician during a consultation with a patient. Once an entry has been created on the EHR system, all the steps from the time the clinician consulted the patient until treatment was administered is tracked and stored by the system, providing a platform for medical errors to be readily identified and corrected; and then re-designed (Hillestad et al., 2005). Utilising electronic records will allow the spread of up-to-date health information across a variation of services to enhance medical practice (Adenuga et al., 2017). EHR use further contributes to improving the decision-making potential for stakeholders such as physicians, healthcare institutions, customers, government, policymakers, and academia (Hossain et al., 2019).

2.2.2.1.3 PRODUCTIVITY

Through using an effective EHR system, desired levels of efficiency, productivity, quality of healthcare, and customer satisfaction can be reached (Sebetci, 2018). IT, such as the EHR, is also able to enhance productivity through minimising needless iterative processes by expanding the utilisation of computers, efficient information provision, and data mining systems. The modernisation of work processes will ultimately improve the policies and standards of health organisations (Sebetci, 2018), and is considered an indispensable product in supporting routine operations in hospitals (Bawack & Kamdjoug, 2018).

Hillestad et al. (2005) looked to other industries – banking, retail, telecommunications, security – which diverted a large amount of budget spend towards IT in the 1990s. These industries reported a significant increase, up to eight percent, of year-on-year productivity growth. However, the authors reiterate that if the healthcare industry is to experience such growth, the degree of transformation must coincide with advances towards HIT implementation. Critical ingredients that necessitate productivity growth – such as investments into EHRs, increased competition on price and quality, infrastructure developments, change-driving institutions, and integrated, standardised systems – are usually lacking in the healthcare system (Hillestad et al., 2005). Safi, Thiessen, and Schmailzl (2018) cite productivity as a fundamental reason as to why consumers accept the EHR. For the healthcare industry to realise positive social returns from EHR implementation, the technological intervention must be coupled with effective organisational change management (Agha, 2014).

2.2.2.1.4 PATIENT OUTCOMES

Reducing harm and improving patients' safety and overall health outcomes remains a primary focus for health care systems worldwide (Brenner et al., 2016). However, literature investigating the role of EHRs absolutely improving patient health outcomes has mixed reactions. Nonetheless, EHR systems play an outstanding role in supporting clinicians, reducing human medical errors, improving medical care standards, patient care, and health outcomes (Sebetci, 2018). Sebetci (2018) further asserts that these systems have an impact on reshaping existing bureaucratic structures by reducing the red tape in health institutions, shifting internal coordination, and enhancing decentralisation and overall organisational coordination. This has a positive effect on time-wastage, further improving the quality of patient care and a reduction in waiting times.

On average, the EHR has seen a 3% reduction in the overall length of hospital stays and the rate of readmissions, especially in patients with associated comorbid diseases (Wani & Malhotra, 2018). The EHR may also be the critical next step in the chronic disease surveillance of chronic asthma, diabetes mellitus and hypertension through multisite collaboration (Tarabichi et al., 2020).

2.2.2.2 DISADVANTAGES AND BARRIERS TO EHR ADOPTION

Many barriers exist that impede the adoption and effective implementation of HIT systems (Hillestad et al., 2005). Owing to the recent movement toward EHR systems, there is a lack of information supporting the absolute usefulness of the system following its implementation and its effects on factors such as workflow efficiency (Tall, Hurd, & Gifford, 2016). Given that EHRs may negatively affect patient outcomes, consideration of its limitations of the system should be applied prior to its application and implementation in medical practice. The following sub-sections will explore, from existing studies, the most cited limitations of the EHR system.

2.2.2.2.1 HIGH INITIAL AND ONGOING COSTS

The high initial cost of HIT system implementation could serve as a barrier towards adopting this technology, and the time spent on implementation has a negative effect on productivity and patient satisfaction (Tall et al., 2015). Evidence confirming EHR's potential to reduce healthcare costs remain inconsistent (Sadoughi et al., 2018). Sadoughi, Khodaveisi, and Ahmadi (2018) further assert that although 50% of studies support the cost benefits of HIE implementation, a number of studies in their systematic review cited HIE's cost-effectiveness as non-significant.

A study by Agha (2014) discovered that from 1998 to 2005, the implementation of HIT made little progress towards achieving cost-reducing outcomes. The author adds that the return on HIT investment will not be realised until organisational change occurs, and incentives for healthcare providers improve. Dranove et al. (2012) confirm this, stating that between 1996 and 2009, healthcare facilities that adopted the EMR did not experience the cost-effective benefits of the system. Although EMR implementation may be associated with high initial investment and operating costs, a cost reduction of up to 3.4

percent can be seen three years post-implementation if healthcare facilities with a degree of IT know-how (Dranove et al., 2012).

2.2.2.2.2 LEGAL AND REGULATORY IMPLICATIONS

The ethical and legal dilemmas involved in EHR adoption and use are prevalent on a global scale. The urgency to adhere with the Protection of Personal Information (POPI) Act (No 4 of 2013) is intensifying within the South African healthcare context (Kandeh, Botha, & Futcher, 2018). Patient records contain highly confidential information about patients, such as their demographics, psychiatric medical conditions, sexual history, as well as current diagnoses of chronic ailments (Heart et al., 2017). Access to such classified information could potentially lead to social embarrassment and stigma if found in the wrong hands (Heart et al., 2017). A study by Badran (2019) found that the idea of having clinicians access their personal medical records was not welcomed by 15% of survey respondents.

As healthcare providers are increasingly adopting the use of HIT to improve their productivity and patient data management, the POPI Act has raised a series of concerns regarding the collection, storage and sharing of patient's personal data; further impeding the adoption of the technology (Katurura & Cilliers, 2016). The issue is that policies often lag behind major technological trends, such as telemedicine and EHRs. Kantura and Cilliers (2016) added that the healthcare industry should see a rise in privacy management courses to facilitate healthcare providers regarding the implementation by-laws of the POPI Act. This is to ensure care providers act per the Act when handling the private information of patients who use electronic platforms for health-related purposes (Katurura & Cilliers, 2016). The role of perceived security is imperative to the adoption of HIT (Hsu et al., 2013).

2.2.2.2.3 PHYSICIAN BURNOUT

Physician burnout - a state in which clinicians lose confidence and a sense of success in their work – has been recently declared a global health crisis (Jha et al., 2019). Individual and organisational factors, such as a rapidly changing healthcare economy coupled with a shift in the patient-encounter, has intensified the pressures on healthcare leaders and care providers (Shanafelt et al., 2016). The consequences of physician burnout include

increased medical errors, threats to patient and physician safety, and healthcare workforce turnover. As physicians struggle to keep up with the demands of complex work environments, their dissatisfaction with the usability of EHRs concerning Meaningful Use has only exacerbated burnout rates (Jha et al., 2019). Following the implementation of the HITECH Act, the typical role and workflows of a physician have been dominated by the EHR – a major "pain point" in their daily practice (Jha et al., 2019, p.4). As eloquently stated across literature, the broader implications of electronic environments on healthcare providers require observation to avoid the adverse effects on the physician and, overall, improve professional job satisfaction needed to produce patient care that is safe and efficient.

2.2.2.2.4 INTERFERENCE WITH THE PATIENT ENCOUNTER

Effective patient-physician communication lies at the centre of building sustainable patient-physician relationships, which is the heart of clinical medicine and patient health outcomes (Rathert, Mittler, Banerjee, & McDaniel, 2017). Concerns have been raised about the influence of the EHR on distorting the communicative element clinicians have with their patients (Rathert et al., 2017). However subtle EHR's role is in changing patient or physician behaviour, its implications on the emotional and non-verbal cues physicians are trained to notice during patient encounters. These cues are essential to establishing patient trust and rapport (Rathert et al., 2017).

2.2.2.2.5 LACK OF INFRASTRUCTURE

In 2012, the South African National Department of Health released a 2012 to 2016 national eHealth strategy to facilitate the requirements of health digitisation in the country. Katurura and Cilliers (2018) echoed the same sentiments on healthcare infrastructure being a critical success factor (CSF) for ensuring the EHR is successfully implemented across South African healthcare facilities. Furthermore, various EHR systems are implemented and maintained by a variety of independent vendors. Each EHR system operates in isolation, functioning on different databases that fail to efficiently communicate and distribute information (Katurura & Cilliers, 2018). The lack of interoperability across various EHR systems is a barrier to the adoption of the technology.

2.3 End User's Intentions Toward EHR Systems

To understand why some clinicians adopt and use HIT systems and others resist, studies have analysed the intentions of physicians toward new technology. The Theory of Reasoned Action (TRA) was the first to introduce behavioural intention (Fishbein & Ajzen, 1977). From the TRA, also known as the Theory of Planned Behaviour (TPB), intention is classified as the amount of effort an individual exerts in order to achieve a set-out objective (Ajzen, 1991). In the TPB, intention is determined by one's attitude and level of social influence, whereas one's sense of being in control affects their attitude, social influence, and behaviour (Ajzen, 1991). Other researchers have utilised frameworks, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) model, to perform an in-depth analysis of the factors influencing end-users' intentions to adopting technology (Adenuga et al., 2017; Alam, Hoque, Hu, & Barua, 2020; Bawack & Kamdjoug, 2018; Hoque & Sorwar, 2017; Macedo, 2017).

The adoption of HIT systems by clinicians is considered as one of the greatest challenges. A variety of issues have been examined regarding IT systems, and the reasons clinicians resist or fear technology (Ayanso et al., 2015). Sebetci (2018) asserts that user intentions are directly associated with their satisfaction with the EHR. Social influence, facilitating conditions, and performance expectancy also influence user intentions towards technology adoption (Adenuga et al., 2017).

A cross-sectional survey study by Hossain et al. (2019) was conducted on 300 clinicians across public and private healthcare facilities in Bangladesh to determine their intentions towards the EHR. The authors discovered that the adoption of the EHR was influenced by variables such as social influence, facilitating conditions, and personal innovativeness. The authors had intended to confirm the role of resistance to change on behavioural intention after identifying it as a critical success factor for EHR adoption. However, they failed to test the variable empirically. They attributed the failure to the youthfulness of their sample as resistance is more prevalent in the elderly (Hossain et al., 2019).

Other studies have analysed the implications of a clinician's demographics, such as gender, age, and years of medical experience, in understanding its impact on technology adoption and use. For example, in 2007, Simon et al. (2007) performed a state-wide survey on clinicians' use of the EHR system in the U.S. The results of their study revealed that physicians who adopted EHRs were younger, had just recently graduated and had

practiced medicine for fewer years in comparison to the non-adopters. Further, specialists and clinicians who worked in large medical practices showed better use of the EHR system following implementation (Simon et al., 2007).

Other studies analysed the adoption rates between developed and developing countries to explain the different influences focussing on external factors (environment) and individual factors (attitude). Gajanayake, Ianella and Sahame (2016) investigated the adoption of a new genre of eHealth in Australia, created to manage the privacy concerns of the eHealth system – Accountable-eHealth (AeH). From the responses received from students, nurses and medical doctors, the authors found that performance expectancy and attitude had a profound, significant effect on behavioural intention toward AeH adoption (Gajanayake, Ianella, & Sahame, 2016).

A study by Cohen, Bancilhon, and Jones (2013) investigated e-prescribing adoption and acceptance barriers in South Africa from a user trust perspective. They found that clinicians showed clear intentions of using e-prescribing if the opportunity was made available. Furthermore, performance expectancy and facilitating conditions had a significant impact on behavioural intention while trust and effort expectancy had a significant negative impact on clinicians' intentions to accept the technology (Cohen, Bancilhon, & Jones, 2013). However, this study places little focus on the role of individual factors such as clinicians' attitudes and resistance to change.

In contrast to the pre-adoption and implementation phase, research in the post-adoption phase is limited. In a Canadian study by Ayanso, Herath, and O'Brien (2015), which focuses mainly on the post-adoption phase of EHR implementation, it was found that very little literature explains the behaviours of clinicians, their satisfaction with the system and intentions to continue to use the technology. Clinicians' continuance intentions of EHR (Ayanso et al., 2015), as well as the impact of using reinforcement incentives to motivate clinicians' ongoing use of technology, is poorly understood (Adenuga et al., 2017). An important finding in the study by Kim, Lee, Hwang, and Yoo (2016) is that clinicians exhibit positive intentions towards IT only if it improves workflow efficiency. Although many may adopt the EHR, some remain cautious of the system.

The advantage obtained from the implementation of innovation is having a clear indication that users of the technology will accept and use it. Since clinicians are the key stakeholders in the use of EHR systems, their adoption and utilisation of these systems

will have long term effects in expediting the improvement of healthcare delivery (Hossain et al., 2019).

2.4 Theoretical Foundations and Conceptual Model

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

Research on technology adoption and use, especially in the field of informatics, has become increasingly relevant in recent years. The Technology Acceptance Model (TAM) was the first model that has been widely cited to explain adoption in IT research (Davis, 1989). Thereafter, many researchers adapted the TAM to improve its explanatory power by hypothesising various antecedents to technology acceptance (Dasgupta & Gupta, 2019). This formed the foundation of new, integrative models. Based on the literature, a widely accepted model, the UTAUT, was found to outperform individual models and is viewed as the most statistically efficient for investigating behaviour towards technology in various contexts of healthcare (Venkatesh, et al., 2003; Ward, 2013). Because EHR is still regarded as a new emerging technology in developing economies, there is a glaring paucity of knowledge and published research investigating the determinants of this new cost-effective and efficient technology (Badran, 2019). Therefore, the UTAUT model formed the cornerstones of this research to quantitatively evaluate the antecedents predicting the adoption of the EHR in South Africa.

The UTAUT model was developed over a decade ago, in response to the use of inconsistent models and constructs under the subject of technology adoption. The IS and IT fields have extensively utilised the model in various studies and research developments (Venkatesh et al., 2016). The UTAUT was derived from a synthesis of eight theories to examine behavioural intentions towards technology. The “Innovation Diffusion Theory; Theory of Reasoned Action; Technology Acceptance Model; Theory of Planned Behaviour; combined TAM-TPB; Model of Personal Computing (PC) Utilisation; Motivational Model; Social Cognitive Theory, and; Unified Model of E-government Adoption” (Ayanso et al., 2015; Hoque & Sorwar, 2017; Hossain et al., 2019, p. 78; Venkatesh et al., 2003). The outcome of the cross-examination of the models mentioned above and theories was achieving a more coherent view of end-user adoption to amplify the quality of future research (Venkatesh et al., 2003).

The UTAUT's explanatory power is superior to that of models such as the TAM in explaining 77% of the variance in behavioural intention and 52% of the variance in technology usage (Venkatesh et al., 2016). Hossain et al. (2019) found that most studies discovered the key driver of intention to be users' attitudes towards technology. The authors further assert that past researchers have attempted to investigate the antecedents affecting users' intentions towards technology adoption by use of the UTAUT (Hossain et al., 2019).

The core constructs of the UTAUT was tailored to the current research and based on the analysis of previous studies applying the UTAUT in the healthcare sector. Figure 1 illustrates the basic components of the UTAUT model. There are four known components of the UTAUT model: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) which all act as predictors for users' behavioural intention (BI) in technology adoption (Venkatesh et al., 2003). The known moderating variables of the model are age, gender, medical experience, and use voluntariness, all of which predict BI and the actual use of technology in organisational settings (Venkatesh, Thong, & Xu, 2016). According to the original model, PE, EE, and SI determine BI to use technology, whereas FC and BI determine the actual use of technology (Venkatesh et al., 2003).

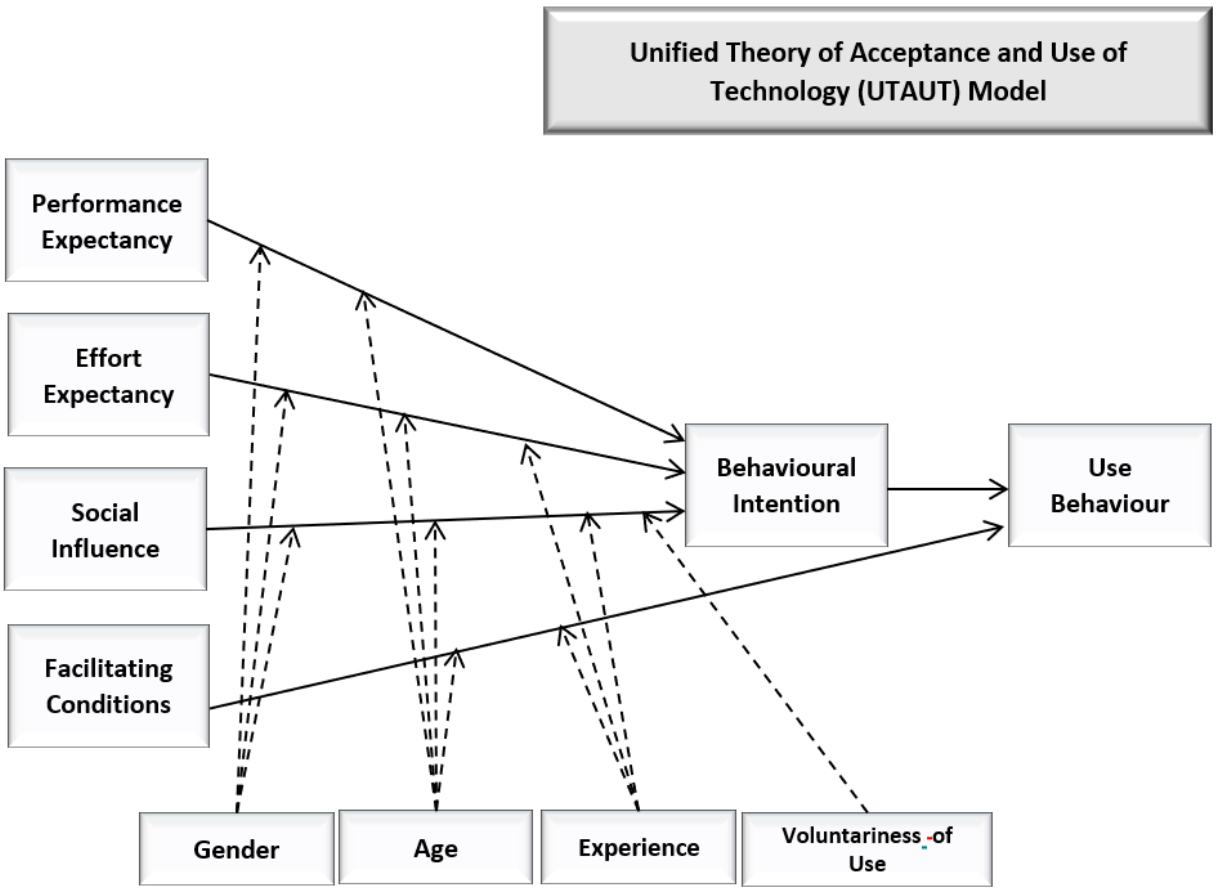

Figure 1: The Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003)

The model is a practical tool for health care managers or leaders to assess the degree of technology acceptance and use within healthcare organisations (Dasgupta & Gupta, 2019). The model further assists in understanding the antecedents that are the drivers and barriers of BI, technology acceptance and use; to inform the technology providers of the technological features requiring attention or adjustment to better suit the users. The succeeding chapter should explain the hypotheses adapted for the current study to investigate clinicians' BI towards the EHR in South Africa.

2.5 Chapter Summary

This chapter has reviewed literature on the importance of healthcare innovation, taking into consideration the adoption of HIT systems and the drivers of EHR adoption. The section also reviewed the end-user's intentions toward EHR systems, the theoretical foundations, and the conceptual model underpinning this study. Chapter 3 outlines the

hypotheses developed in this study for measuring clinicians' BI towards the EHR in South Africa.

CHAPTER 3: RESEARCH QUESTIONS AND HYPOTHESIS DEVELOPMENT

As stated in previous chapters, the purpose of this research served to answer the following overarching question: what are the key determinants of the adoption and use of healthcare technology in the South African context? Technology adoption in emerging settings is unique as challenges, such as the uneven distribution of resources, contributes substantially to a digital divide, poor existing infrastructure, and cultural beliefs of new technology (Bawack & Kamdjoug, 2018). These countries are of interest to researchers as few studies have been carried out in these contexts adding to the relevancy and necessity for investigating the topic of technology adoption (Bawack & Kamdjoug, 2018). The following sections illustrate the established hypotheses for this study.

3.1 MEASURED CONSTRUCTS

3.1.1 PERFORMANCE EXPECTANCY (PE)

PE refers to the degree of benefit a person believes they will receive through the use of the technology (Venkatesh et al., 2003). PE "reflects the utilitarian value of the technology for users" (Badran, 2019, p.582). Venkatesh et al. (2003) found PE to be the most crucial predictor of an individual's BI to adopt the technology. This was confirmed by Hoque and Sorwar (2017), who further suggests that in cases of a higher PE, new technological advances are more likely to be adopted. Therefore, the following hypothesis was developed from the stated argument:

Hypothesis 1. PE will have a positive influence on clinicians' intentions to use the EHR (Venkatesh et al., 2003).

3.1.2 EFFORT EXPECTANCY (EE)

EE refers to the degree of effort a person exerts to use new technology (Venkatesh et al., 2003). EE significantly predicts clinicians' BI toward new technological systems such as telemedicine (Adenuga et al., 2017). Hossain et al. (2019) further emphasise the direct influence of EE on the user's intentions towards using the EHR. Therefore, the following hypothesis was developed from the stated argument:

Hypothesis 2. EE will have a positive influence on clinicians' intentions to use the EHR (Venkatesh et al., 2003).

3.1.3 SOCIAL INFLUENCE (SI)

SI is the degree of importance a person places on the beliefs of others and how this influences their decision to use technology (Venkatesh et al., 2003). Hossain et al. (2019) suggest that SI positively influences clinicians' BI to accept new IT in healthcare in addition to other eHealth services. Therefore, the following hypothesis was developed from the stated argument:

Hypothesis 3. SI will have a positive influence on clinicians' intentions to use the EHR (Venkatesh et al., 2003).

3.1.4 FACILITATING CONDITIONS (FC)

FC refers to the degree a person perceives that the necessary support and resources, such as technical infrastructure, exists to use technology (Venkatesh et al., 2003). Adenuga, Iahad, and Miskon (2017) state that FC combines constructs from three technology adoption models: "perceived behavioural control, FC, and compatibility" (p. 89). Infrastructure plays a critical role in supporting HIS (Bhattacherjee & Hikmet, 2008). FC is also found to directly influence clinicians' intentions towards technology use (Hossain et al., 2019). However, according to Bawack and Kamdjoug (2018), literature on HIS adoption in developing economies found a direct positive correlation between FC and BI. Therefore, the following hypothesis was developed from the stated argument:

Hypothesis 4. FC will have a positive influence on clinicians' intentions to use the EHR (Bawack & Kamdjoug, 2018).

3.2 RESEARCH MODEL

Figure 2 illustrates a revised version of the original UTAUT that formed the underpinnings of the current study (Venkatesh et al., 2003). In alignment with the aim of the present study, one additional construct, highlighted in red, will be added to the model.

This research focuses solely on the BI of clinicians towards EHR use and adoption in healthcare. In developing settings, low adoption rates amongst medical professionals followed by underutilised facilities have been reported (Mengesha & Garfield, 2019). Therefore, as Bawack and Kamdjoung (2018) corroborate, context-specific variables are added to the model. Furthermore, it is imperative to understand the critical determinants of technology adoption and use by investigating the antecedents that predict BI.

3.2.1 THE ROLE OF RESISTANCE TO CHANGE

The healthcare landscape is rapidly changing. To upkeep with the rapid change, healthcare facilities are tasked with the implementation and management of change processes. Resistance to change is often seen as an impediment to effective transformation and improvement (Oreg, 2017). Oreg's (2003) view of change resistance is based on an individual's disposition, adding that some individuals are more inclined to resist change than others based on their personality. Hossain et al. (2019) disclose that resistance to change (RC) is defined as either an employee's behaviour in response to an external situation that is associated with feelings of "fear, doubt and uncertainty" in the workplace or merely a reflection of character (p. 80). The successful implementation of health technologies is dependent on acceptance by key stakeholders (Safi, Thiessen, & Schmailzl, 2018). Safi et al. (2018) further suggest that resistance - a psychological indicator of technology acceptance - and its associated factors should be readily identified amongst medical staff to overcome failures to accept technology in healthcare.

The same sentiments on RC were shared by Hossain et al. (2019). Furthermore, despite their research suggesting a strong but negative correlation between RC and BI toward technology use, results from their study showed no significant relationship between the two constructs (Hossain et al., 2019). As resistance to change is prominent in older individuals and a proven barrier to successful HIT implementation, the study may have been flawed as the majority of their study participants were young clinicians less than the age of 40 (Hossain et al., 2019).

Of immense interest to the current study is the significant negative influence of RC on the correlation between BI and technology use (Shahbaz et al., 2019). Due to the South African context, with the decentralisation of healthcare imminent, resistance to change would be an important construct to consider, especially to investigate any variance

between clinicians employed in the private and public institutions. Therefore, to increase the explanatory power of the UTAUT, an additional hypothesis will be added:

Hypothesis 5. Resistance to change will have a negative influence on clinicians' intentions to use the EHR (Hossain et al., 2019)

3.2.2 THE ROLE OF ATTITUDE TOWARDS CHANGE

Resistance to change is often viewed in a negative light (Oreg, 2018). To keep up with the digital era and new technologies, organisations are required to manage and adequately execute the process of change (Oreg, 2018). Previous studies have taken a unfaceted view in understanding the concept of resistance, but Oreg (2006) argues that much is lost taking this approach. The author further endorses that resistance:

> Be viewed as a multidimensional attitude towards change comprising of affective, cognitive, and behavioural components. Taking this view is more likely to encapsulate the complexity behind resistance to change, to provide a deeper understanding of the relationships between resistance, its antecedents, and its outcomes (Oreg, 2006, p.74).

To measure the construct resistance to organisational change, Oreg's Change Attitude Scale (CAS), was utilised as it incorporates the complexity or tri-dimensional aspect of resistance. The scale has been validated; its internal reliability tested through previous studies and has shown to predict change-related behaviour more than other personality characteristics (Oreg, 2018).

According to Hackman and Lawler (1971), as cited by Barrett (2018), the job characteristics model (JCM) proposes that employees determine their job attributes using their individual need states. The adaptation of these needs to observed job characteristics leads to positive work attitudes, while differences lead to negative job attitudes. For example, during the implementation of EHRs in a care facility, as clinicians have very little control over the EHR requirements (standardisation) of record-keeping and the chosen vendor and platform to implement the EHR system, this may threaten their perception of job control – their autonomy. A physician with high levels of autonomy have negative attitudes and will often resist organisational change (Adenuga et al., 2017; Barrett, 2018).

Therefore, the stated argument has led to the development of the following hypothesis:

Hypothesis 6. A negative attitude toward change will have a positive influence on resistance to change (Oreg, 2006)

Thus, the modified UTAUT is proposed in Figure 2.

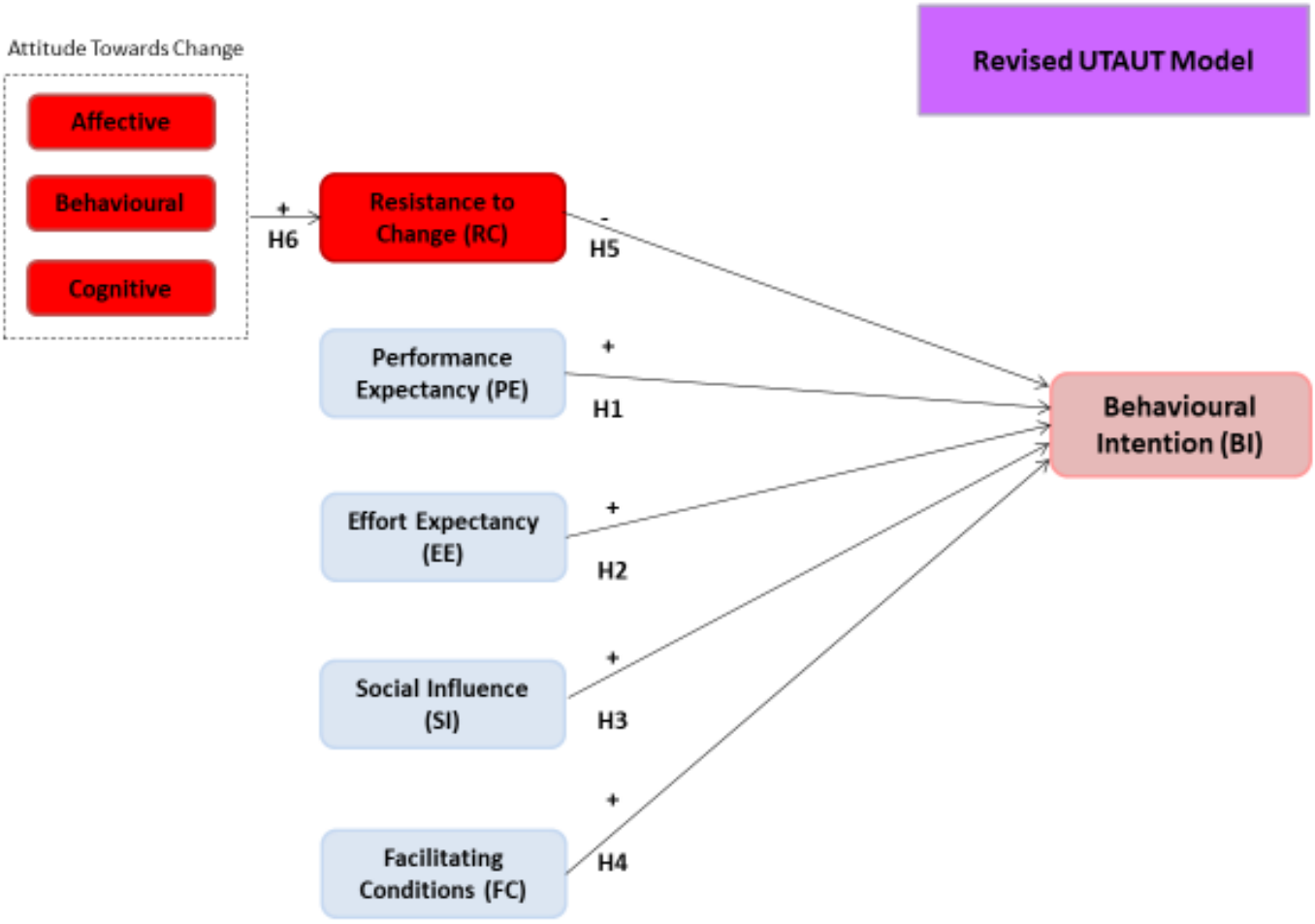

Figure 2: Revised UTAUT Model adapted from (Bawack & Kamdjoug, 2018; Hossain et al., 2019; Oreg, 2006; Venkatesh et al., 2003)

CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

4.1 INTRODUCTION

This chapter outlines the research design and methodology used to address the overarching research question and objectives of this study, as described in Chapter 3. The World Health Organization (2019) stated that the adoption rates of the EHR are much lower in lower-middle to low-income countries. The concept of the underutilisation phenomena of HIT in developing countries is not well understood (Mengesha & Garfield, 2019), and knowledge of the factors influencing adopters' perceptions and intentions towards HIT in a developing setting, is lacking (Adenuga et al., 2017). Hence, the research technique elected to investigate this concept was mono-method and quantitative in nature. Although the combination of the two approaches to research in business studies is common, it is neither superior, desirable, practical nor time-saving (Bryman et al., 2014).

The chapter of this mono-method quantitative study is structured as follows:

Section 4.1 provides an introduction to the nature and timeline of the current study;

Section 4.2 addresses the research design and defends the research method selection;

Section 4.3 provides a detailed evaluation of the context in which the research was conducted, as well as the target population elected, to yield the desired results as demonstrated in Chapter 5;

Section 4.4 addresses the sampling method used for this study as well as the sample size required for the statistical analysis outlined in Chapter 5;

The remainder of the chapter builds on section 4.4 by describing the measurement tools used and the approach taken to perform statistical analysis.

4.2 RESEARCH DESIGN

The investigation into the variables which influence clinicians' intentions toward the EHR was achieved by adopting the dominant method for conducting business-type research – the quantitative method (Bryman et al., 2014). The research method sought to address

the following overarching research question: what are the key determinants of the adoption and use of healthcare technology in the South African context?

From the various types of research methods, a researcher has to identify the most suitable approach to inquiry (Creswell, 2006). Qualitative study is a research methodology that, as opposed to quantitative, usually highlights words in the data gathering and analysis phases (Bryman et al., 2014). Characteristic of quantitative research, it was essential to emphasise the key concepts in this study that were defined linearly in terms of four characteristics: measurement, causality, generalisation and replication (Bryman et al., 2014).

The present study undertook a deductive approach (the most common reasoning used in quantitative studies) to evaluate a well-known technology acceptance theory, the UTAUT (Saunders & Lewis, 2018). According to Saunders and Lewis (2018), an explanatory type of study centers on the relationships between variables or constructs. Using variables from theoretical aspects of previous research, this descriptive study sought to unfold the relationships between the independent variables (PE, EE, SI, FC and ATC) and the dependant variables (RC and BI) (Creswell, 2006). In addition to the UTAUT, a behavioural psychology tool, Oreg's CAS, was used to bring more significance to the field of resistance. As quantitative research draws on the interconnections between theory and practice, this was the most appropriate single method suited for this type of study (Bryman et al., 2014).

In addition, the use of existing theories to test hypotheses 1 through 6, as described in Chapter 3, is characteristic of a positivist paradigm (Saunders & Lewis, 2018). This choice of philosophy is aligned to the purpose of this research, which aimed to understand the impact of the measurable variables on clinicians' intentions towards EHR adoption. Further, to establish the nature of these relationships, this study reproduced commonalities and variances across multiple responses (Saunders & Lewis, 2018).

Furthermore, the cross-sectional time horizon was most applicable as this study analysed the data from a specific population group at a particular period - also known as a 'snapshot' (Saunders & Lewis, 2018, p.130). The appropriate strategy adopted for this study, to attain information, involved the collection of primary data through an online source. The technique adopted for this research took place using a structured online questionnaire. The variables were measured and represented in a number format to explain the

relationships guided by existing theory. Creswell (2014) suggested that this non-experimental research design proposes a numerical explanation of the views or trends of a studied sample population. The validity and reliability of the research instrument are explained below, together with the analysis approach.

This research design was appropriate for this study as it allowed the researcher to ask multiple participants (South African clinicians) the same set of questions in a manner that was analogous and fair. The design allowed the lucrative collection of a large volume of data that was comparable and to be analysed systematically (Saunders & Lewis, 2018). In addition, the design offered respondents autonomy and confidentiality when answering questions during a time that was most suitable for the respondent (Saunders & Lewis, 2018).

4.3 Population

South Africa's healthcare system is comprised of the private and public systems, the latter of which is usually underfunded and under-resourced (Winchester & King, 2018). The public health sector services the majority of the population (almost 85%) with the private system servicing the remainder (Neely & Ponshunmugam, 2019). Most clinicians work in public healthcare facilities. Some clinicians in public health settings, like Khayelitsha Hospital, do have some exposure to or existing knowledge of a HIT system such as the Clinicom Emergency Medical Record (Ohuabunwa et al., 2016). Furthermore, doctors working in the well-funded private healthcare sector most likely utilise IT as part of their daily work routine.

Due to these factors, the target population of this study was qualified clinicians with experience in both private and public hospitals from various regions in South Africa, as they are the key stakeholders in EHR use and adoption. Clinicians were the primary target as they are the leading users of EHR in healthcare institutions. Due to the premise that if their intentions towards technology adoption are positive, they are most likely to become enablers of the technology through recommending it to their patients (Adenuga et al., 2017).

Furthermore, from previous literature in developing contexts, the predicting power of the UTAUT model increases with the age of the clinician acting as the single moderating variable in the context of HIT (Bawack & Kamdjoug, 2018). Also, younger clinicians do not

experience any resistance to adopting new technologies (Hossain et al., 2019), and are far more willing to adopt the EHR system than their older counterparts (older than 40 years) (Bawack & Kamdjoug, 2018). It would be beneficial to perform a comparative study between two age groups of clinicians (those younger and older than 40), especially as higher resistance to change occurs in older clinicians (Hossain et al., 2019). However, as the definition highlighted inherent personality traits and attitude as the pillars of resistance, the purpose of this research did not necessitate investigating the moderating factors of the original model.

The survey instrument was distributed to the target population. The target population comprised of all qualified medical doctors which included: junior medical doctors (interns and community service doctors), medical officers, registrars and a variety of specialists (emergency and trauma specialists, cardiologists, ophthalmologists, neurologists, paediatricians, anaesthetists, surgeons, physicians, obstetricians, and gynaecologists to name a few).

4.3.1UNIT OF ANALYSIS

The units of analysis for this study were individuals (qualified clinicians) across various departments and specialty levels in the healthcare sector in South Africa. These individuals, as stated previously, are the key deciding stakeholders in utilising electronic health platforms due to their ability to influence technology use within the healthcare community (Ayanso et al., 2015). Therefore, the data required for this study was collected from these individuals.

4.4 Sampling Method and Size

This study involved collecting and analysing primary data. Sampling intends to generate findings that can be translated to an entire population group. However, it was not possible to reach all qualified clinicians in the healthcare sector in South Africa. The healthcare industry in South African is large and dispersed across regions ranging from those easily accessible and those remotely inaccessible. A complete and comprehensive sampling frame of all healthcare professionals was not easily attainable. Therefore, a practical approach to sampling was taken for the purpose and time-constraints of this study. The best technique to achieve optimal results was through probability testing (Saunders &

Lewis, 2018). However, this research did not fulfill the requirements of probability testing, and therefore, the sampling technique most suitable for this study that best enabled the research question was the purposive non-probability technique (Saunders & Lewis, 2018).

Individuals suitable for the study were identified through personal judgment, reasoning, and the researcher's social, academic, and work contacts. Only individuals who matched the criteria for a qualified clinician, a practicing medical professional with a certified medical degree, was used for the study as they would be able to provide the correct answers needed to achieve the objectives of this research. From this, a list of potential participants and their respective email addresses was compiled as a channel for distributing the online cover page, letter, and questionnaire. Further, to increase the number of responses received, the snowball sampling method was most appropriate to achieve this objective.

In addition, to increase the rate of response, the South African Medical Association (SAMA), a professional, non-statutory association representing medical practitioners in both the private and public sectors, was contacted to utilise their existing database as a means to circulate the questionnaire to medical practitioners. The SAMA database comprises of a total of 17 500 members in the country (SAMA Annual Report, 2014). The questionnaire was circulated to clinicians on the existing database.

Obtaining the correct sample size was an essential component of quantitative research. For data to be regarded as statistically relevant, as a rule of thumb, the sample size should be five times the number of variables used in the analysis with an acceptable ratio of cases to variables being 10:1 (Ho, 2006). Alternatively, a round figure of 200 is considered an appropriate sample size, whereas 300 is a good sample size to conduct statistical analysis using Structural Equation Modelling (SEM) (Hoelter, 1983; Hossain et al., 2019). However, this is dependent on the size of the sample population. Approximately 25 clinicians were purposefully selected to snowball the questionnaire to other clinicians in their network strategically. The estimated reach of the survey was 250 respondents.

4.5 Measurement Instrument

An online questionnaire was used for the survey as most clinicians would have some form of access to either a portable computer, smartphone, or tablet device. The questionnaire

included a letter of informed consent, demographic type questions, details of work experience followed by the standard questionnaire. The questionnaire was based on the UTAUT model by Venkatesh et al. (2003), and additional questions in the areas of resistance (Hossain et al., 2019) and behavioural psychology from Oreg's CAS (Oreg, 2006) were used. A structured questionnaire was utilised for this study to obtain information from the selected population group in a language familiar to the group. The questions used in the instrument targeted clinicians' intentions toward HIT systems. All questions, apart from those used in the demographics section, were evaluated on a five-point Likert scale, which was operationalised by other researchers. The scale measured responses on a range from "strongly disagree," represented by 1, to "strongly agree," represented by 5. The components of the Likert scale are illustrated below:

Table 1

Components of the five-point Likert scale

1	Strongly disagree
2	Disagree
3	Neutral
4	Agree
5	Strongly Agree

Theoretical constructs measured in the survey were adapted from previous literature on HIT adoption and resistance to change. The questions used were arranged logically from demographics leading into more direct inquiries related to clinicians' intentions toward HIT. Items were grouped according to each construct to minimise the influence on responses. See *Appendix 2*.

4.5.1 MEASURES

THE UTAUT MODEL

Based on the literature, a widely accepted model, the UTAUT, was found to outperform individual models and is viewed as the most statistically efficient for investigating behaviour towards technology acceptance in healthcare (Ward, 2013; Venkatesh et al., 2003). Hossain et al. (2019) found that the UTAUT was popularised as a result of previous scholarship utilising the model in determining the antecedents to user intentions towards

technology adoption. There are four known constructs of the UTAUT model: PE, EE, SI and FC (Venkatesh et al., 2003). The model and its constructs, as stated in Chapter 3, have been validated through previous research and tested using a five-point Likert scale. Items from this model are shown in *Appendix 3*.

THE CHANGE ATTITUDE SCALE (CAS)

To investigate resistance to organisational change, Oreg's CAS was used as it incorporated a multi-dimensional approach to the study of resistance (Oreg, 2006). The scale includes an employee's affect toward change, behaviour towards change, and cognition of change. The original scale contained 15 items; however, this was adapted for this research based on the results of the pre-test.

4.5.2 RESEARCH ETHICS

This study has ethical approval from the Research and Ethics Committee of the Faculty of Health Sciences at the University of Pretoria. This study used the underpinnings of pre-existing models and measurement instruments: the UTAUT model and questionnaire from Venkatesh, Morris, G.B. Davis, F.D. Davis et al. (2003) and the CAS from Oreg (2006). Permission to use the content from the authors was granted. In addition, permission was received from the copyright owners (the publisher) to reproduce the material specified above. Furthermore, permission was granted from SAMA to utilise their database to circulate the online questionnaire to their existing members (practicing clinicians employed in public and private institutions).

4.5.3 QUESTIONNAIRE PRETESTING

The complete questionnaire contained 35 items, including the demographics and the variables related to the research question. The purpose of the pre-test was to not only to confirm the validity and reliability of the instrument but to detect and correct errors in the design of the questionnaire prior to its distribution. In addition, the pre-test served to ensure that respondents had no difficulty in understanding the questions (Saunders & Lewis, 2018).

The test was conducted on ten qualified clinicians who were close networks within the researcher's social circle. These clinicians were entrusted with the task of providing honest feedback on the questionnaire design. Issues regarding incorrect or confusing wording and rhetoric were highlighted. From the questionnaire, the reverse coded questions were flagged, and the pre-test group preferred a mixture of both positive and negative questions, as opposed to all negatively worded questions. Overall, the feedback approved of the overall questionnaire in answering the relevant hypotheses. Furthermore, the pre-test group advised adding excluding questions to safeguard against individuals completing the questionnaire out of curiosity and not based on their experience using the EHR.

The group also confirmed that the time taken to complete the questionnaire was less than 10 minutes. This was an important element to consider as to not further burden already busy clinicians with a lengthy questionnaire.

4.6 Data Gathering Process

The data for this research was proposed to be collected over three to four months. However, due to the limitations of this study, to be discussed in Chapter 7, the data collection period occurred over two months. As already stated, the web link to the survey was emailed to study participants and distributed through social networks, such as WhatsApp and LinkedIn. The online survey was used as a primary data collection tool. The source of data collection for this study was gathered by the online survey on the Google Forms platform.

To increase the rate of response, clinicians were regularly reminded to complete the survey through email, direct telephone calls, and messaging. The above techniques allowed for data to be collected from 168 respondents. All respondents completed the questionnaire. However, this figure does not reflect the number of partially completed questionnaires as the study design did not allow this.

4.7 Analysis Approach

Conclusions were based on the findings obtained from analysing the data collected from the study. As this study utilised a Likert scale, the numeric data was expressed in intervals according to the scale (Saunders & Lewis, 2018). For the quantitative analysis of data,

data cleaning techniques were first applied using Microsoft Excel and tabulated according to completed responses. Answers to the questions that used the Likert scale were replaced by their correspondent numeric value of the answer. For example, “strongly disagree” was substituted by one (1) and “strongly agree” substituted by five (5). Thereafter, summarised tables were imported into statistical analysis software such as Statistical Package for Social Sciences (SPSS version 25) to examine the data appropriately. The statistical analysis generated frequencies, factor analysis, correlations and regression analysis for the responses.

4.7.2 VALIDITY TESTING

The measurement instrument used for this study, as discussed in Chapter 3, was made up of several constructs that give insight into clinicians’ BI towards the EHR. As stated in section 4.5.1, the questions were formulated using a number of scales. Prior to performing a detailed statistical analysis using SPSS version 25, the suitability of the test items, which form the basis of the research questions, was assessed. This was done through exploratory factor analysis. Exploratory factor analysis – “a data reduction technique”- is used to examine the validity of the variables by exploring the interrelationships between test items (Pallant, 2013, p. 190). To help assess the factorability of the data presented and whether the factor analysis was appropriate for this study, Bartlett’s test, a measure of sphericity, and the Kaiser-Meyer-Olkin (KMO) index, a measure of the adequacy of the sample, were used (Pallant, 2013). According to Pallant (2013), a KMO value greater than .5 and Bartlett’s test of sphericity at a p-value < .05 is desirable.

The exploratory factor analysis also detects whether items under each construct grouped with other associated construct items. The factor analysis assumes that any variable may be associated or group under any factor, respectively. This serves to verify whether each variable was allocated to its correct factor. To ensure the validity of the measured constructs, items used for the measurement of latent constructs were adapted from prior studies to incorporate the new constructs about this study (Hossain et al., 2019).

4.7.2 RELIABILITY TESTING

To ensure reliability, this research adopted collection methods and various methods of analysis to yield consistent results (Saunders & Lewis, 2018). To measure internal reliability, the Cronbach's alpha (α) test was applied to the relevant data sets.

The measurement model was assessed with respect to its internal reliability, validity, convergent, and discriminant validity (Hossain et al., 2019). One of the most important indicators used to test reliability is by the Cronbach's α coefficient – a test which ascertains whether the variables in the measurement model have consistent responses (Pallant, 2013). A level of .7 and above is advisable (Bawack & Kamdjoug, 2018; Hossain et al., 2019). However, levels above .8 are preferable (Pallant, 2013). According to previous researchers, Venkatesh et al. (2003) and Oreg (2006), both the UTAUT and Change Attitude Scales, mentioned in section 4.5.1, have good internal reliability, with a Cronbach's α coefficient reported of .80 and .88 respectively. Both scales, according to Pallant (2013), having preferred levels of reliability.

4.7.3 DESCRIPTIVE STATISTICS

Following validity and reliability testing, descriptive statistics were performed on the data for each Likert scale question in the measurement model using SPSS version 25. Statistics were calculated and tabulated for each test item to gain an understanding of how participants responded to each question. The mean scores: which described how each question was responded to on average and the minimum scores: which revealed the average lowest score was determined. Furthermore, the maximum score: the highest average score and; the standard deviation: which indicated how much each question differed from the mean – a sign of variance of the data (Wegner, 2012) were established.

Each question used in the measurement model would be allocated a mean, minimum, maximum and standard deviation score.

4.7.4 PARTIAL LEAST SQUARES METHOD

Prior studies have utilised a standardised tool for data analysis across multiple constructs of the proposed research model. An example is Structural Equation Modelling (SEM), a statistical method which comprises of the Partial Least Squares (PLS) method, where the initial data captured on excel is transferred to additional software (Hossain et al., 2019).

PLS is favoured in previous studies as “it does not impose sample size restrictions and is distribution-free” (Bhattacherjee, Hikmet, 2007, p. 6); and measures constructs according to their R squared scores (Alam et al., 2020). However, this method was not used for this study as a sample size of 300 and above is required, which was not the expected reach survey respondents, detailed in section 4.4.

4.7.5 MULTIPLE REGRESSION ANALYSIS

Standard multiple regression was used to assess the ability of two control measures (the UTAUT model and Oreg’s CAS) to predict clinicians’ BI towards EHR adoption. As a confirmatory measure to ascertain whether laws of normality, linearity and multicollinearity were not breached, a provisional analysis was undertaken (Pallant, 2013). Multiple regression analysis, which has been dubbed as a “family of techniques,” was the technique of choice utilised by the researcher to better understand the relationships between the two dependent variables and the multiple independent variables of this study; in order to test various hypotheses for significance (Pallant, 2013, p.146).

There are eight basic requirements for multiple regression analysis, which includes testing eight assumptions. The first two assumptions relate to the data and choice of study design, while the remaining six indicate the degree of fit between the data and the empirical model (Pallant, 2013).

In this current study, the dependent variables are RC and BI (Figure 2). The remaining variables are all considered independent. The results of the multiple regression analysis were interpreted by examining whether the model was a good fit and the statistical significance of the measurement model was critiqued at a 95% confidence interval.

CHAPTER 5: DATA ANALYSIS AND RESULTS

5.1 INTRODUCTION

Chapter 5 provides insight into the results obtained from the online survey based on the experiences of respondents using the EHR. The following sections and sub-sections will address the method of data analysis from data collection to statistical analysis, and then conclude the findings in relation to the research question pertaining to this study, as in Chapter 3. First, the frequencies and descriptive analyses are described. This is accompanied by the demographics of the study participants. Thereafter, construct validity and reliability of the measurement instrument used in this study are then explained. Then the results from various tests examining the interrelationships between constructs investigating BI towards the EHR are presented. Each section will show the most prominent findings as per the researcher's interpretation.

5.2 FREQUENCIES AND DESCRIPTIVE ANALYSIS

The demographic characteristics of the respondents are illustrated in Table 2. After data cleaning techniques were applied to improve the quality of the data, of a total of 168 responses, only 122 responses were considered as valid for data analysis and interpretation. The remaining respondents, 27% (n=46), indicated that they had no current or previous experience using the EHR system and, therefore, did not qualify to continue to completion of the survey. For the survey analysed, of the total of 122 responses, 54.1% (n=66) of respondents were male, and 45.9% (n=56) were female. The distribution of the respondents, by age and gender, are further illustrated in Figure 3.

The majority of the respondents (23.8%) were older than 55 years of age, followed by the 31 to 35 age group, which comprised 16.4% of the total number of respondents. The target population consisted of clinicians currently employed in public or private healthcare institutions across South Africa. For a respondent to be considered as a valid participant, they were required to specify their area of specialisation and the number of years of experience in medicine. Of the 122 responses, 57% of respondents were specialists in the surgery, emergency medicine, family medicine, obstetrics and gynaecology, paediatrics, internal medicine, occupational medicine, and public health fields; while 43% were general practitioners. In addition, 91.8% of clinicians had more than three years of

experience in medicine, 53.3% had more than three years' experience using IT in their daily practice, and 89.3% of respondents indicated they were voluntarily willing to use the EHR system in the future (Figure 4).

Table 2

Demographics of respondents.

Variable	Description	Frequency	Percentage
Gender	Male	66	54,1%
	Female	56	45,9%
Age (in years)	Less than 25	1	0,8%
	25-30	18	14,8%
	31-35	20	16,4%
	36-40	15	12,3%
	41-45	17	13,9%
	46-50	10	8,2%
	51-55	12	9,8%
	More than 55	29	23,8%
Medical specialization	General Practice	52	42,6%
	Family Medicine	8	6,6%
	Paediatrics	4	3,3%
	Medicine Specialist	10	8,2%
	Obstetrics & Gynaecology	7	5,7%
	Orthopaedics	4	3,3%
	Occupational Medicine	4	3,3%
	Surgery	19	15,6%
	Anaesthesiology	3	2,5%
	Junior Doctor	1	0,8%
	Emergency medicine	3	2,5%
	Public Health	2	1,6%
	Other (psychiatry, forensic pathology, oncology)	5	4,1%
Medical Experience	Less than 1 year	1	0,8%
	1-3 years	9	7,4%
	4-6 years	19	15,6%
	7-9 years	10	8,2%
	More than 10 years	83	68,0%
IT usage in healthcare	Less than 1 year	9	7,4%
	1-3 years	48	39,3%
	7-9 years	9	7,4%
	More than 10 years	56	45,9%
Willingness to use EHR	Yes	109	89,3%
	No	4	3,3%
	Maybe	9	7,4%
Experience using the EHR	Yes	122	100%
	No	46	0%

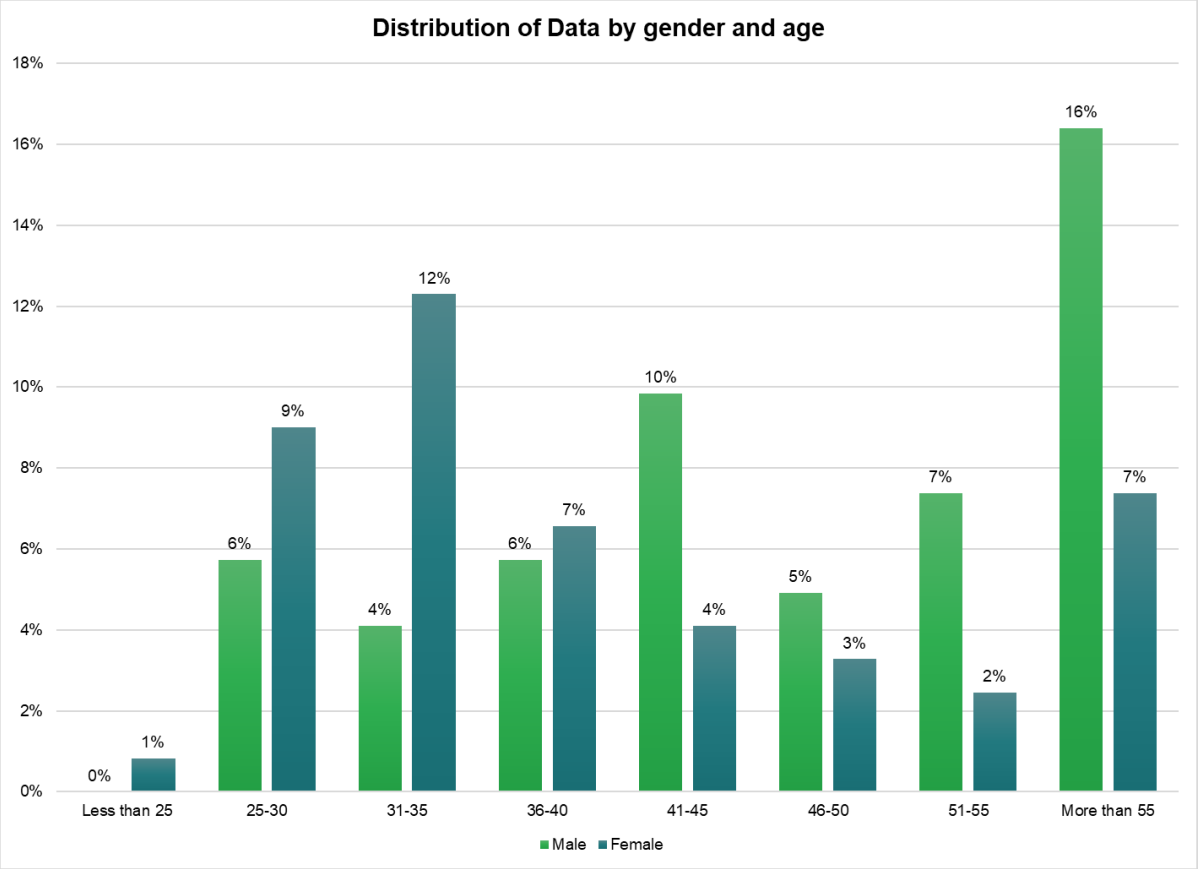

Figure 3: Distribution of data by gender and age

5.3 Test Item Analysis

The frequency of the responses for the model items was sorted according to their means and illustrated in the stacked bar chart shown in Figure 4. The majority of respondents perceived the test items in the behavioural portion of attitude towards organisational change (B1, B2, and B4), questions related to respondents protesting against change, preventing change, or presenting their objections towards change, negatively (M = 1.66, SD = 1.027). On the opposite extreme of the scale, BI-1 and BI-2 – questions relating to respondents' ongoing or future use of the electronic health record – were positively responded to (M = 4.39, SD = 0.914). This alludes to a more optimistic stance of respondents towards the use of EHRs in the future.

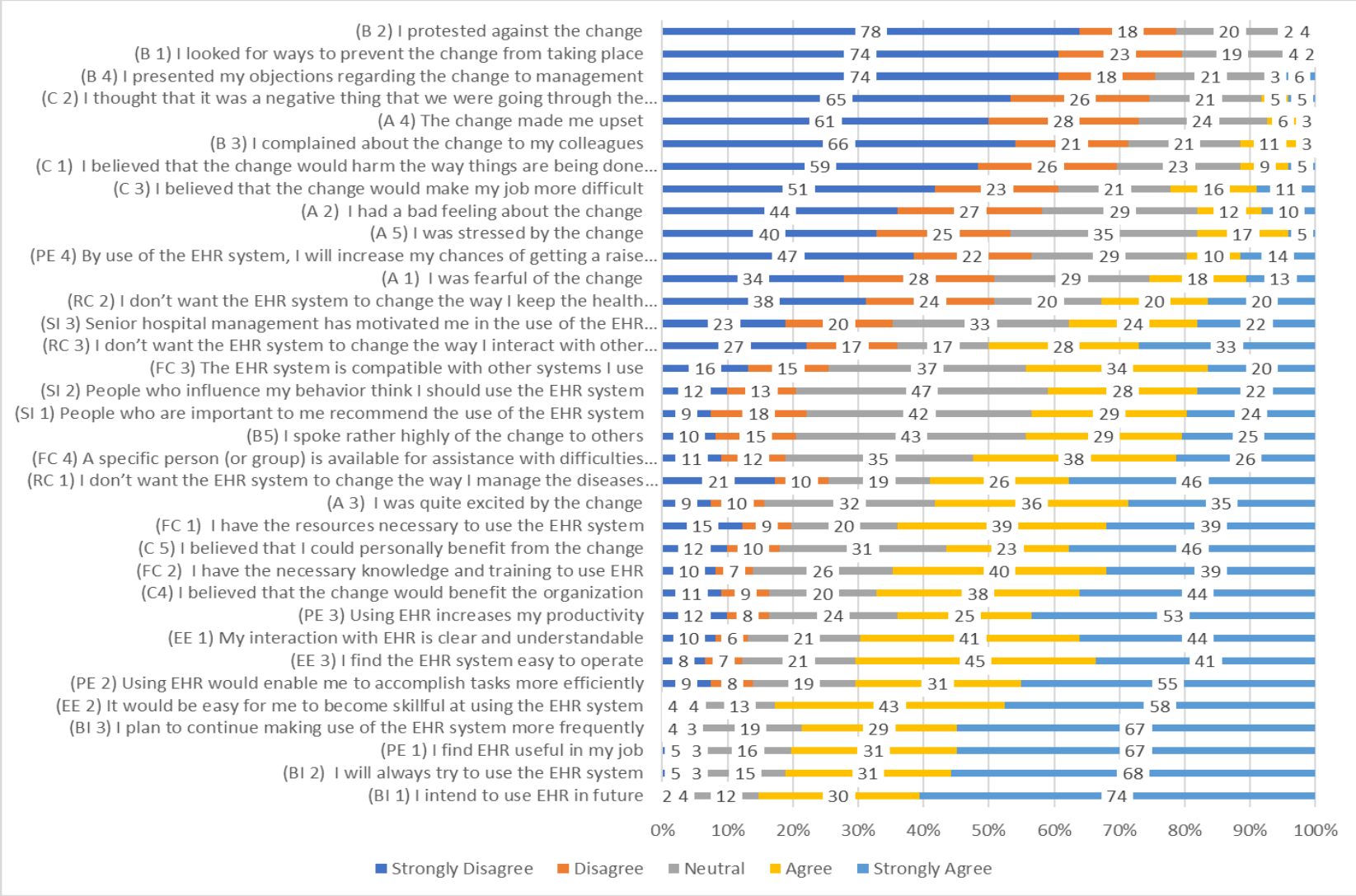

Figure 4: Frequencies of test item responses arranged according to means (lowest to highest)

5.4 Construct Validity

Prior to performing a detailed statistical analysis using SPSS version 25, the suitability of the test items was assessed through exploratory factor analysis. Bartlett's test, and the Kaiser-Meyer-Olkin (KMO) index were used to establish the degree of factorability of the data (Pallant, 2013).

5.4.1 KAISER MEYER OLKIN (KMO) AND BARTLETT'S TEST FOR SPHERICITY

5.4.1.1 UTAUT MODEL (PART B) ITEMS

Inspection of the correlation matrix in Appendix 4 highlighted multiple coefficients of .3 and above. The results of the KMO index and Bartlett's test are shown in Table 3. The KMO index was .845, which exceeded the minimum and recommended value of .5 (Pallant, 2013). The result for Bartlett's test of sphericity reached statistical significance at a p-value of .000 (less than the level of significance of p< .05). Both values support the factorability of the correlation matrix.

Table 3

KMO and Bartlett's test results for Part B Items

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0,845**
Bartlett's Test of Sphericity	Approx. Chi-Square	1302,800
	df	136
	Sig.	**0,000**

The anti-image correlation matrix, as illustrated in Appendix 5, is informative and should be studied in addition to the KMO values (Field, 2013). The diagonal elements of the anti-image correlation matrix, which represents the KMO index for individual variables, were all above the minimum required value of .5. As all values were in excess of the bare minimum, no variables were excluded from the statistical factor analysis (Field, 2013).

As a result of all test items being retained, the variance of each item is explained by the communalities extraction using principal axis factoring. Communalities for principal axis represents the aggregate influence of all test items on its variable component. The normal

values for communalities range between zero and one, where zero indicates that a variable cannot be predicted by any of its factors, and one where a variable can be wholly defined by all its factors – representing no uniqueness (Field, 2013). Furthermore, low values, less than .3, is an indication that that test items do not fit well with other items in its construct (Field, 2013). Questions PE4 and SI3 had values of .278 and .261 respectively (Appendix 5). Values close to one are more desirable as this demonstrates that the measurement tool is a reflection of the observed dataset. Therefore, questions PE4 and SI3 are not as highly predictable from other variables in the dataset.

5.4.1.2 ATTITUDE TO ORGANISATIONAL CHANGE SCALE ITEMS (PART C)

Similarly, as in section 5.4.1.1, an inspection of the correlation matrix in Appendix 4, highlighted multiple coefficients of .3 and above. The results of the KMO and Bartlett's test are shown in Table 4. The KMO index was .871, which exceeded the minimum and recommended value of .5 (Pallant, 2013). The result for Bartlett's test of sphericity reached statistical significance at a p-value of .000 (less than the level of significance of p< .05) at a 95% confidence interval. Both values support the factorability of the correlation matrix.

Table 4

KMO and Bartlett's test results for Part C Items

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0,871**
Bartlett's Test of Sphericity	Approx. Chi-Square	1063,458
	df	105
	Sig.	**0,000**

The diagonal elements of the anti-image correlation matrix, which represents the KMO index for individual variables, were all above the minimum required value of .5. As all values were more than the bare minimum, no variables were excluded from the statistical factor analysis (Field, 2013).

All test items were retained, and the variance of each item explained by the communalities extraction using principal axis factoring. Communalities for principal axis represents the aggregate influence of all test items on its variable component. The normal values for communalities range between zero and one, where zero indicates that a variable cannot

be predicted by any of its factors, and one where a variable can be wholly defined by all its factors – representing no uniqueness (Field, 2013). Communalities for all test items were above the bare minimum of .3, indicating that the test items fit well with other items in its construct (Field, 2013).

5.4.1.3 BEHAVIOURAL INTENTION ITEMS (PART D OF UTAUT MODEL)

Similarly, as in section 5.4.1.1, an inspection of the correlation matrix in Appendix 4 highlighted multiple coefficients of .7 and above. The results of the KMO and Bartlett's test are shown in Table 5. The KMO index was .760, which exceeds the minimum and recommended value of .5 (Pallant, 2013). The result for Bartlett's test of sphericity reached statistical significance at a p-value of .000 (less than the level of significance of p< .05). Both values support the factorability of the correlation matrix.

Table 5

KMO and Bartlett's test results for Part D Items

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		**0,760**
Bartlett's Test of Sphericity	Approx. Chi-Square	381,853
	df	3
	Sig.	**0,000**

The diagonal elements of the anti-image correlation matrix, which represents the KMO index for individual variables, were all above the minimum required value of .5. As all values were in excess of the bare minimum, no variables were excluded from the statistical factor analysis (Field, 2013).

All test items were retained, and the variance of each item explained by the communalities extraction using principal axis factoring. Communalities for all test items were above the bare minimum of .3, indicating that the test items fit well with other items in its construct (Field, 2013).

5.4.2 EXPLORATORY FACTOR ANALYSIS RESULTS

5.4.2.1 UTAUT MODEL (PART B) ITEMS

Principal axis factoring was the extraction method used, and the factor rotation was set to varimax normalised. Principal axis factoring revealed the presence of four factors with eigenvalues exceeding the value of one, explaining 40.0%, 13.2%, 9.9%, and 7.3% of the variance, respectively (Table 7). This contrasts with the five factors formulated in the theoretical model used for this study, as discussed in Chapter 3. Factor loadings >.6 are emphasised in red and are grouped into their respective components (Table 6), which make up a total of 70.52% of the variance explained (Table 6). An inspection of the scree plot showed a distinct break after the fourth component (Appendix 6). This is supported by the total variance explained, which showed four components with eigenvalues exceeding the Kaiser criterion values (Field, 2013).

Table 6

Factor Loadings (Varimax Normalised) Pattern or Structure Coefficients (Part B)

Test Item	Factor 1	Factor 2	Factor 3	Factor 4
PE2	**0,882**	0,181	0,122	0,076
PE3	**0,864**	0,102	0,142	0,092
PE1	**0,798**	0,234	0,154	0,101
EE3	**0,770**	0,425	0,051	0,123
EE1	**0,668**	0,499	0,081	0,124
EE2	**0,600**	0,347	-0,067	0,017
FC3	**0,479**	0,452	-0,067	0,180
PE4	**0,432**	0,108	0,083	0,270
FC2	0,397	**0,779**	-0,034	0,098
FC1	0,327	**0,761**	-0,076	0,049
FC4	0,155	**0,640**	0,074	0,301
rRC3	0,067	-0,018	**0,844**	0,012
rRC2	0,068	0,110	**0,710**	0,157
rRC1	0,100	-0,116	**0,685**	0,000
SI2	0,204	0,043	0,056	**0,907**
SI1	0,396	0,149	0,117	**0,645**
SI3	-0,046	0,133	0,022	**0,491**

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.[a]

a. Rotation converged in 6 iterations.

Table 7

Total Variance Explained UTAUT model (Part B)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**6,807**	40,041	40,041	6,490	38,178	38,178	4,485	26,380	26,380
2	**2,251**	13,239	53,281	1,861	10,946	49,124	2,527	14,863	41,243
3	**1,691**	9,947	63,228	1,324	7,789	56,913	1,799	10,581	51,824
4	**1,240**	7,295	**70,523**	0,903	5,311	62,224	1,768	10,399	**62,224**
5	0,838	4,927	75,450						
6	0,757	4,454	79,905						
7	0,631	3,710	83,615						
8	0,498	2,929	86,543						
9	0,406	2,390	88,934						
10	0,365	2,148	91,082						
11	0,334	1,963	93,044						
12	0,291	1,715	94,759						
13	0,245	1,444	96,203						
14	0,211	1,238	97,441						
15	0,209	1,229	98,670						
16	0,149	0,878	99,547						
17	0,077	0,453	100,000						

Extraction Method: Principal Axis Factoring

As highlighted in Table 6, the test items load almost completely into their respective components. In factor 1, PE, EE and FC loaded onto the same factor. All questions, apart from PE4, EE2 and FC3, have a coefficient value above .6, which confirms a high level of association among these questions. PE, which is the degree of benefit a person believes they will receive through the use of the technology, is a powerful predictor of clinicians' BI towards EHR adoption (Venkatesh et al., 2003).

EE, the degree of effort a person exerts to use new technology, also positively affects clinicians' intentions toward new technological systems (Venkatesh et al., 2003). The test item FC3 – 'the EHR is compatible with other systems I use' – refers to how a clinician perceives the adequacy of existing infrastructure to support EHR use (Venkatesh et al., 2003). A clinician is likely to perceive the performance of the technology with the amount of effort required to become skilful at using the EHR. Whereby an EHR system that is high performing requires little effort to use and is widely compatible with any other technological system involved in the treatment of patients. Consequently, this makes it highly possible that the questions from the three constructs are statistically associated. However, the face validity of the questions suggests three separate constructs. As PE, EE and FC were all hypothesised to test their respective components; the constructs were measured separately as referenced in the theoretical model proposed in Chapter 3. The researcher,

however, remained cautious during the interpretation of the results measuring PE, EE, and FC.

The questions PE4, EE2, and FC3 have coefficient values below .5 but above the minimum threshold of .3. Only PE4 had a low communality value, as described in section 5.4.1. The construct reliability of the test items measured by the Cronbach's α, to be explained in the following sections, was used to determine if the item lowered the reliability of its component. Indeed, if the item lowered the reliability of the variable, this would warrant the removal of the question from the construct (Field, 2013).

Factor 2 contains questions related to the construct FC, apart from FC3, FC1, FC2, and FC4 had coefficient values above .6, which is above the minimum threshold. These questions had communalities above the level of .5, as identified in section 5.4.1.

Factor 3 contains questions related RC – questions that are negatively correlated with clinicians' intentions towards the EHR. As resistance tests for clinician's behaviour in response to an external situation and is associated with negative feelings of fear, doubt and uncertainty, these questions were reverse coded (Hossain et al., 2019). These test items have coefficient values above .6, confirming the high level of association among these questions.

Factor 4 contains questions related to SI. SI had a positive impact on clinicians' intentions to adopt the EHR. The degree of importance a clinician places on the beliefs of others will ultimately affect their adoption of healthcare technology and other eHealth services (Venkatesh et al., 2003). All questions in this factor have coefficient values greater than .6, apart from SI3 – a question relating to the motivating role of senior management in encouraging the use of the EHR system in their healthcare facility. Questions SI1 and SI2 have coefficients above .6 and are highly associated with each other. Further, test item SI3 has a low communality value of .261, as mentioned in section 5.4.1. Therefore, the results from the Cronbach's alpha documented in the next sections will be used to determine if the question contributes positively to the reliability of its measured construct.

All hypotheses formulated for the four constructs of Part B of the UTAUT model questions, namely: PE, EE, SI and FC, are associated in measuring their components, thus confirming the validity of the instrument by factor analysis.

5.4.2.2 ATTITUDE TO ORGANISATIONAL CHANGE ITEMS (PART C)

For Part C's test items, the Attitude to Organizational Change scale, principal axis factoring was the extraction method used, and the factor rotation was set to varimax normalised. Principal axis factoring revealed the presence of 3 factors with eigenvalues exceeding the value of one (Table 8), explaining 44%, 13.7% and 8.4% % of the variance respectively (Table 9). Factor loadings > .6 are emphasised in red and are grouped into their respective components. An inspection of the scree plot showed a distinct break after the third component (Appendix 7). This is supported by the total variance explained, which showed the component with an eigenvalue exceeding the Kaiser criterion values (Field, 2013).

Table 8

Factor loadings (Varimax Normalised) pattern or structure coefficients (Part C)

Test Items	Factor 1	Factor 2	Factor 3
B2	**0,842**	0,061	0,124
B3	**0,799**	0,220	0,251
A4	**0,722**	0,061	0,364
C2	**0,692**	0,236	0,268
B4	**0,689**	0,215	0,033
C1	**0,656**	0,208	0,324
B1	**0,638**	0,126	0,318
C3	**0,519**	0,291	0,449
rC5	0,117	**0,884**	0,104
rC4	0,137	**0,774**	0,073
rB5	0,127	**0,580**	-0,005
rA3	0,161	**0,539**	0,141
A1	0,156	0,004	**0,781**
A2	0,339	0,158	**0,708**
A5	0,413	0,126	**0,503**

Extraction Method: Principal Axis Factoring.
Rotation Method: Varimax with Kaiser Normalization.[a]
a. Rotation converged in 5 iterations.

Table 9

Total variance explained of the attitude to organisational change scale (Part C)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**6,602**	44,016	44,016	6,210	41,398	41,398	4,312	28,748	28,748
2	**2,067**	13,780	57,797	1,663	11,086	52,484	2,349	15,657	44,406
3	**1,261**	8,408	**66,204**	0,880	5,864	58,348	2,091	13,943	**58,348**
4	0,865	5,763	71,968						
5	0,809	5,394	77,362						
6	0,704	4,693	82,055						
7	0,513	3,421	85,476						
8	0,390	2,603	88,078						
9	0,316	2,110	90,188						
10	0,313	2,085	92,273						
11	0,303	2,017	94,289						
12	0,264	1,758	96,048						
13	0,246	1,640	97,687						
14	0,195	1,299	98,987						
15	0,152	1,013	100,000						

Extraction Method: Principal Axis Factoring.

As highlighted in Table 8, the test items do not load completely into their respective components. In factor 1, one affective (A), four behavioural (B), and three cognitive (C) items loaded onto the same factor. All questions, apart from question C3, have a coefficient value above .6, which confirms a high level of association among these questions. Oreg's Attitude to Change Scale (2006) was used to assess resistance to organizational change. Test items A1-A5 denote an employee's affect, or attitude (positive or negative) towards a particular change, such as technology; B1-B5 test items denote an employee's behaviour or communicative reactions towards change; and C1-C5 test items denote an employee's cognition or examination of the change (Barrett, 2018).

B1-B5 were hypothesised to form one variable – behavioural (B) component of ATC. However, B1-4 and B5 load under Factor 1 and Factor 2, respectively. Test items C1-3 refer to the negative effects of change, such as change harming workflows in an organisation. Test item A4 - 'the change made me upset' – refers to an employee's emotional response towards organisational change. Consequently, this makes it highly possible that the questions from the three constructs are statistically associated. However, the face validity of the questions suggests three separate constructs. As test items A, B and C were all hypothesised to test their respective components, the constructs were measured separately as referenced in the theoretical model proposed in chapter 3. The researcher, however, remained cautious during the interpretation of the results measuring PE, EE, and FC.

Factor 2 contains test items A3, B5 and C4-5. C4-C5 had coefficient values above 0.6, which is above the minimum threshold, confirming a high level of association among the questions. Test items A3 and B5 had coefficients above .5 but below .6, respectively. A3 and B5 items had communalities below the level of .5 but above the minimum threshold of .3, as identified in section 5.4.1.2. As stated above, it highly possible that the questions from the three constructs are statistically associated. However, the face validity of the questions suggests three separate constructs.

Factor 3 contains questions related to the affective (A) component of ATC (items A1, A2 and A5). A1-A2 had coefficients above .6, therefore, are highly associated with each other. A5 has a coefficient value above .5 but below .6. This value remains above the minimum threshold of .3.

5.4.2.3 BEHAVIOURAL INTENTION ITEMS (PART D OF UTAUT MODEL)

For Part D of the UTAUT model, principal axis factoring was the extraction method used, and the factor rotation was set to varimax normalised. Principal axis factoring revealed the presence of 1 factor with an eigenvalue exceeding the value of one (Table 11), explaining 91.3% of the variance (Table 10). Factor loadings >.6 are emphasised in red and are grouped into their respective components. An inspection of the scree plot showed a distinct break after the first component (Appendix 6). This is supported by the total variance explained, which showed the component with an eigenvalue exceeding the Kaiser criterion values (Field, 2013).

Table 10

Factor loadings (Varimax Normalised) pattern or structure coefficients for behavioural intention (Part D) Items

	Factor 1
BI2	**0,963**
BI3	**0,950**
BI1	**0,886**

Table 11

Total variance explained for BI (Part D)

Factor	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**2,740**	91,336	**91,336**	2,614	87,148	**87,148**
2	0,176	5,852	97,188			
3	0,084	2,812	100,000			

Extraction Method: Principal Axis Factoring.

As highlighted in Table 10, the test items load perfectly into their respective component. Factor 1 includes all the test items related to BI, which refers to a person's readiness to perform a specific task, such as deciding on the use of new technology (Hossain et al., 2019). All questions have a coefficient above .8, which confirms a high level of association among these questions.

All hypotheses formulated for all ten constructs of the UTAUT model and Oreg's CAS questions, namely: PE, EE, SI, FC, RC, ATC (affective, behavioural and cognitive components) and BI, are associated in measuring their components based on the values mentioned above. Thus, confirming the validity of the instrument by factor analysis.

5.5 Theoretical Measurement Model Reliability

The Cronbach's alpha (α) values assess the internal reliability of the model. Levels above .7 denote internal consistency (Hossain et al., 2019); however, levels above .8 are preferable (Pallant, 2013). The reliability of the measurement tools used in this research is detailed below:

Table 12

Cronbach's alpha (α) values

Variable	Test Item	Cronbach's α if item deleted	Cronbach's α
Performance	PE1	0,804	**0,853**
Expectancy (PE)	PE2	0,743	
	PE3	0,752	
	PE4	0,928	
Effort	EE1	0,822	**0,853**
Expectancy (EE)	EE2	0,859	
	EE3	0,681	
Social Influence (SI)	SI1	0,455	**0,723**
	SI2	0,633	
	SI3	0,802	
Facilitating	FC1	0,764	**0,835**
Conditions (FC)	FC2	0,746	
	FC3	0,838	
	FC4	0,810	
Resistance to Change (RC)	rRC1	0,653	**0,792**
	rRC2	0,744	
	rRC3	0,748	
Change Attitude Scale (ATC)	A1		**0.748**
	A2		
	rA3		
	A4		
	A5		
	B1		**0.788**
	B2		
	B3		
	B4		
	rB5		
	C1		**0.798**
	C2		
	C3		
	rC4		
	rC5		
Behavioural Intention (BI)	BI1	0,911	**0,952**
	BI2	0,916	
	BI3	0,956	

5.5.1 UTAUT MODEL

5.5.1.1 PERFORMANCE EXPECTANCY (PE)

The reliability for the PE construct with four items is acceptable with a Cronbach's α of .853. Table 12 illustrates that deleting the test item, PE4 will improve the Cronbach's α of the construct to .928. In section 5.4.1.1, the communalities for questions PE1-PE3 showed a high level of association for measuring the PE construct. Test item PE4 had a low communality. However, as the Cronbach's α is acceptable and above the level of .8, this item warranted its presence on the scale. Thus, all questions for this construct were used to test the hypothesis related to PE.

5.5.1.2 EFFORT EXPECTANCY (EE)

The reliability for the EE construct with three items is acceptable with a Cronbach's α of .853. Table 12 illustrates that deleting test item EE2 will minimally improve the Cronbach's α of the construct to .859. In section 5.4.1.1, the communalities for questions EE1-EE3 showed a high level of association for measuring the EE construct. Thus, all questions for this construct were used to test the hypothesis related to EE.

5.5.1.3 SOCIAL INFLUENCE (SI)

The reliability for the SI construct with three items is acceptable with a Cronbach's α of .723. Table 12 illustrates that deleting test item SI3 will minimally improve the Cronbach's α of the construct to .802. In section 5.4.1.1, the communality for questions SI3 was low at .261. However, the Cronbach's α with this test item is above the acceptable range. Thus, all questions for this construct were used to test the hypothesis related to SI.

5.5.1.4 FACILITATING CONDITIONS (FC)

The reliability for the FC construct with four items is acceptable with a Cronbach's α of .835. Table 12 illustrates that deleting test item FC3 will minimally improve the Cronbach's α of the construct to .838. In section 5.4.1.1, all questions were highly associated with

above-normal communality values. Thus, all questions for this construct were used to test the hypothesis related to FC.

5.5.1.5 RESISTANCE TO CHANGE (RC)

The reliability for the RC construct with three items is acceptable with a Cronbach's α of .792. Table 12 illustrates that deleting no test items will improve the Cronbach's α value. Thus, all questions for this construct were used to test the hypothesis related to FC.

5.5.1.6 BEHAVIOURAL INTENTION (BI)

The reliability for the BI construct with three items is acceptable with a Cronbach's α of .952. Table 12 illustrates that deleting test item BI3 will improve the Cronbach's α of the construct to .956. In section 5.4.1.1, the communalities for questions BI1-BI3 showed a high level of association for measuring the BI construct. All questions had high communalities and were highly associated. However, as the Cronbach's α is acceptable and above .8, this item warranted its presence on the scale. Thus, all questions for this construct were used to test the hypothesis related to BI.

In summary of the above, section 5.5.1 illustrates Cronbach's α values ranging from .723 to .952, which indicates strong internal reliability. These results are consistent with the results obtained by Hossain et al., (2019), which further supports the reliability of the UTAUT Model constructs in assessing the factors influencing clinicians' intentions towards EHR adoption in a developing country.

5.5.2 ATTITUDE TOWARDS CHANGE SCALE

The measurement model illustrated in Table 12 highlights the estimated Cronbach's α values of the current study ranging from .748 to .798, which indicates strong internal reliability. An abbreviated version of this scale was studied by Barrett (2018) and yielded a Cronbach's α of .91. However, according to Oreg (2006), the complete three-factor scale had reliability scores for the A, B, and C components of .78, .77, and .86, respectively; baring results similar to the current study. Thus, all questions for this scale were used to test the hypothesis related to the attitude towards organisational change scale.

5.6 DESCRIPTIVE STATISTICS FOR VARIABLES AND CONSTRUCTS

The descriptive statistics for each of the test items that make up a variable are explained in the following section. The theoretical scale, as proposed in chapter 3, was used. Using the descriptive statistics, an average score was calculated for each construct. Only responses where all questions were answered were considered for descriptive statistics. The total number of responses is represented by the column labelled 'N' in Table 13.

Table 13

Descriptive statistics for variables and constructs

	(*N*) Valid	Missing	Mean	Median	Mode	Std. Deviation	Minimum	Maximum
PE	122	0	3,5902	3,7500	4,50	1,04301	1,00	5,00
EE	122	0	3,9672	4,0000	5,00	0,98231	1,00	5,00
SI	122	0	3,2131	3,1667	3,00	0,99315	1,00	5,00
FC	122	0	3,5164	3,5000	3,50	1,01728	1,00	5,00
RC	122	0	3,1339	3,3333	3,00	1,25651	1,00	5,00
A	122	0	2,2967	2,2000	2,20	0,85522	1,00	4,60
B	122	0	1,9213	1,7000	1,40	0,80188	1,00	5,00
C	122	0	2,1328	2,0000	1,00	0,92696	1,00	5,00
Attitude towards Change (Total)	122	0	2,1169	2,0000	1,47	0,76211	1,00	4,73
Behavioural Intention	122	0	4,3005	5,0000	5,00	0,95000	1,00	5,00

5.6.1 PERFORMANCE EXPECTANCY (PE)

The PE construct contained four questions which allowed each respondent to account for the degree of benefit an individual believes they will receive using the EHR system to improve their work performance. As discussed in chapter 4, a Likert scale was used to assess the level of PE ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Table 13 shows the average descriptive statistics scores that were used to measure PE. The overall mean score for PE revealed that, on average, respondents somewhat agreed that the EHR system improved their work performance (M = 3.59, SD = 1.04). The minimum score for the construct was 1.00 – which is the strongly disagree option. The score with the highest number of responses, or the modal value, was 4.5. Therefore, the mean is a

fair representation of the responses of the construct and results further confirm that the EHR contains features that improve clinicians' work performance.

5.6.2 EFFORT EXPECTANCY (EE)

The EE construct contained three questions which allowed each respondent to account for the degree of ease related to the use of the EHR system. Reviewing the results in Table 13 shows that the modal option selected for all the questions was option 5 ("strongly agree"). The overall mean score for EE indicates that most clinicians found the EHR easy to use, that they could easily become skilful at using the EHR system, and their interactions with the EHR system, until that point, was clear and understandable (M=3.96, SD = 0.98). Therefore, the mean is a fair representation of the responses of the construct and results further confirm that clinicians' use of the EHR, until then, was associated with ease.

5.6.3 SOCIAL INFLUENCE (SI)

The SI contained three questions related to the degree of importance a respondent placed on the beliefs of others and how that would affect their adoption of the EHR system. Reviewing the results in Table 13 shows that the modal option selected for all the questions was option 3 ("neutral"). The overall mean score for SI indicates that most clinicians' use of the EHR system was not entirely dependent nor independent of the SI encouraging the use of the EHR system (M=3.21, SD = 0.99).

5.6.4 FACILITATING CONDITIONS (FC)

Four test items represented the construct, FC, which measured the degree a clinician perceives that organisational or technical support and resources are available to support EHR use. Reviewing the results in Table 13, the modal option selected for all the questions was option 3 ("neutral"). The overall mean score for FC indicates that most clinicians were somewhat in agreement with the presence of technical and organisational resources to support their use of the EHR (M=3.5, SD = 1.01).

5.6.5 RESISTANCE TO CHANGE (RC)

Three questions in the questionnaire measured the construct RC. In contrast to the other questions which made up the UTAUT scale, resistance is negatively associated and was reverse coded during the exploratory factor analysis. Resistance refers to either an employee's behaviour in response to an external situation that is associated with feelings of "fear, doubt and uncertainty" in the workplace or simply a reflection of character (p. 80). Reviewing the results in Table 13, the modal option selected for all the questions was option 3.5 (the midpoint between "neutral" and "agree"). The overall mean score for FC indicates that most clinicians' were uncertain as to how much interference they would want the EHR system to have on the way they managed their patient's diseases, medical records and referrals (M=3.1, SD= 1.23).

5.6.6 BEHAVIOURAL INTENTION (BI)

Three questions in the questionnaire measured the BI construct. BI denotes a "person's readiness to carry out a specific behaviour" that ultimately influences their decision to act (Hossain et al., 2019, p.79). Reviewing the results in Table 13, the modal option selected for all the questions was option 5 ("strongly agree"). The overall mean score for BI indicates that most clinicians were confident and optimistic about their ongoing future use of the EHR system (M=4.3, SD= 0.95).

5.6.7 AFFECTIVE (A) COMPONENT OF THE CAS

The affect component of the CAS questionnaire contained five questions which allowed each respondent to account for an employee's affect, or attitude (positive or negative) towards a particular change, such as the implementation of an EHR system in the workplace. As this scale measures resistance, questions are negatively associated; meaning, the higher an individual score, the more resistant they are. As discussed in chapter 4, a Likert scale was used to assess the level of PE ranging from 1 ("strongly disagree") to 5 ("strongly agree"). Table 13 reveals a modal value of 2.2 (between "disagree" and "neutral"). The overall mean score for this component revealed that the implementation of the EHR system was not a stressful, unwanted change. Further, clinicians were not as upset by the change process (M=2.29, SD = 0.86).

5.6.8 BEHAVIOURAL (B) COMPONENT OF THE CAS

Five questions tested the B component of the CAS, which measured an employee's behaviour or communicative reactions towards change. Reviewing Table 13 reveals a modal value of 1.7 (between "strongly disagree" and "disagree"). The overall mean score for this component revealed that upon the implementation of the EHR system, clinicians did not look for ways to prevent the change, nor partook in any protests against the change, nor did they complain or raise their objections regarding the change (M=1.92, SD = 0.80).

5.6.9 COGNITIVE (C) COMPONENT OF THE CAS

Five questions tested the C component of the CAS, which measured an employee's cognition or examination of the change. Reviewing Table 13 reveals a modal value of 1.0 ("strongly disagree"). The overall mean score for this component revealed that upon the implementation of the EHR system, clinicians did not believe that the change was negative or would make their lives more difficult (M=2.13, SD = 0.93).

5.7 Hypotheses and Conceptual Model Analysis

5.7.1 CORRELATION BETWEEN VARIABLES

5.7.1.1 UTAUT SCALE

The results for Pearson correlation, a parametric approach, are shown in Table 14. The correlations between PE, EE, SI, FC, RC and BI were investigated using Pearson product-moment correlation coefficient.

No violation of the assumptions of normality, linearity, and homoscedasticity was detected. A normal correlation coefficient value ranges between -1.00 to 1.00, which indicates the strength of a correlation. A correlation of 0 indicates no relationship, where -1 shows a perfect negative relationship (Pallant, 2013). Pallant (2013) further suggests following the guidelines offered by Cohen (1988), who state that a small correlation is found in a range of .10 to .29, a medium correlation between .30 to .49 and a large or strong correlation between .50 to 1.0 (p. 132). The correlation between the variables in this study is demonstrated in Table 14.

Table 14

Preliminary Pearson product-moment correlations between variables for UTAUT

	BI	PE	EE	SI	FC	RC
BI	**1.00**	0,726**	0,661**	0,334**	0,606**	-0,242**
PE		**1.00**	**0,771****	0,372**	0,541**	-0,217**
EE			**1.00**	0,319**	**0,734****	-0,107
SI				**1.00**	0,348**	-0,142
FC					**1.00**	-0,013
RC						**1.00**

** Correlation is significant at $p < .01$ (1-tailed)

Multiple regression "does not like multicollinearity" (Pallant, 2013, p. 149). Multicollinearity denotes a strong and significant correlation between the independent variables, where the correlation coefficient is above .9. Reviewing Table 14, EE highly correlates with PE and FC. Pallant (2013) suggests that independent variables that are highly correlated (r of .7 and above) should not be included in the same analysis. If this occurs, consideration should be given to omit the troublesome variable or creating an alternative variable. Using the rules of the common denominator, EE is commonly and unacceptably highly correlated with PE and FC, which may warrant its removal.

From the results of the factor analysis, PE, EE, and FC grouped highly under the same factor – Factor 1. This suggests that there may be multicollinearity issues with the conceptual model hypothesised in Chapter 3.

To confirm this, Table 15 is reviewed – the collinearity diagnostics of multiple regression analysis. Two values are important, Tolerance and VIF. As tolerance is a measure of the degree of variability of an independent variable that is not explained by the remaining independent variables, using the 1 – R squared equation, a small value (less than .10) suggests a high correlation between the variables indicating multicollinearity (Pallant, 2013). Furthermore, VIF values greater than 4 requires investigation, while VIF values higher than 10 denote serious multicollinearity. EE has the highest VIF (3.813) and the lowest tolerance (.262) levels; however, both values are not higher than the cut-off limits postulated by Pallant (2013); therefore, the multicollinearity assumptions were not violated.

Table 15

Structural model

Variable	B	*Beta	t (122)	p-value	Tolerance	VIF
(Constant)	1,782		5,661	0,000		
PE	0,462	0,507	5,291	0,000	0,371	2,697
EE	0,030	0,031	0,273	0,785	**0,262**	**3,813**
SI	0,012	0,013	0,200	0,842	0,820	1,219
FC	0,282	0,302	3,432	0,001	0,438	2,283
RC	-0,093	-0,123	-2,026	0,045	0,929	1,077

B: Unstandardized beta

*B: Standardised beta

Concerning Table 16, the condition indices at the smallest eigenvalue above the threshold value between 15 to 30 are highlighted. EE has a condition index of 15.161, which denotes possible multicollinearity. As a result, to avoid a problematic spurious result, the item EE was removed from the remainder of this study.

Table 16

Collinearity diagnostics

	Eigenvalue	Condition Index	Variance Proportions (Constant)	PE	EE	SI	FC	RC
1	5,695	1,000	0,00	0,00	0,00	0,00	0,00	0,00
2	0,169	5,812	0,00	0,02	0,00	0,02	0,01	0,58
3	0,066	9,288	0,00	0,03	0,02	0,77	0,05	0,00
4	0,035	12,711	0,09	0,24	0,00	0,04	0,55	0,00
5	0,025	**15,161**	0,86	0,20	0,00	0,13	0,01	0,41
6	0,010	23,346	0,05	0,51	0,97	0,04	0,38	0,00

Table 17

Reproduced Pearson product-moment correlations between variables for UTAUT

	BI	PE	SI	FC	RC
BI	**1,000**	0,726**	0,334**	0,606**	-0,242**
PE		**1,000**	0,372**	0,541**	-0,217**
SI			**1,000**	0,348**	-0,142
FC				**1,000**	-0,013
RC					**1,000**

** Correlation is significant at $p < .01$ (1-tailed)

A positive correlation exists between the various constructs, except for RC, which is negatively correlated with all the other variables. All correlation coefficients are positive at p< .01, except for the correlation between RC and SI (r = -0.142, p = .06) and FC (r = -.013, p= .446).

For the positive relationships identified, a strong correlation (above .5) was identified between the following variables:

PE and BI (r = 0.726, p < .01) are strongly correlated, suggesting that from the respondents who participated in this study, the degree of benefit a clinician believes they will receive through the use of the EHR system to improve their work performance impacts their readiness to adopt or use the EHR.

PE and EE (r = 0.771, p < .01) are strongly correlated, thus suggesting that the degree of benefit a clinician believes they will receive through using the EHR system is dependent on the degree of ease related to using the EHR.

FC and BI (r = 0.606, p< .01) are strongly correlated, thus suggesting that clinicians' readiness to adopt or use the EHR is related to the degree a clinician perceives that organisational or technical support and resources are available to support EHR use.

A strong correlation exists between FC and PE (r = 0.541, p< .01), thus suggesting that the degree of benefit a clinician believes they will receive through the use of the EHR is related to the presence of organisational or technical infrastructure available to support EHR use.

A small but significant negative relationship was identified between resistance to change and BI (r =-0.242, p< .01) and between RC and PE (r = -0.22, p< .01). This suggests that the more negative feelings (fear, doubt and uncertainty) clinicians harboured towards the

EHR system, the less open they would be to adopt or using the EHR in the future. Furthermore, the more negative clinicians were towards the EHR system, the lower their beliefs that they will personally benefit from using the EHR system.

5.7.1.2 OREG'S CHANGE ATTITUDE SCALE (CAS)

Table 18

Pearson product-moment correlations between variables for CAS

		RC	ATC
Pearson Correlation	RC	1,000	0,287
	AC	0,287	1,000
Sig. (1-tailed)	RC		0,001
	AC	0,001	
N	RC	122	122
	AC	122	122

** Correlation is significant at $p < .01$ (1-tailed)

The Pearson product-moment correlation coefficient explored the correlation between ATC (determined by the CAS) and RC (determined by the UTAUT model). No violation of the assumptions of normality, linearity, and homoscedasticity were detected by initial testing. A small but significantly positive correlation was found between the RC and ATC ($r = 0.29$, $n = 122$, $p < .0.01$). Therefore, a high score of a negative attitude is linked to a high score of resistance.

5.7.2 MULTIPLE REGRESSION ANALYSES

Standard multiple regression was used to assess the predictability of the two control measures (CAS and the UTAUT Model) in clinicians' BI towards EHR adoption. No violation of the assumptions of normality, linearity, and homoscedasticity was detected by initial testing (Pallant, 2013). Multiple regression analysis, which has been dubbed as a "family of techniques," was used to better understand the relationships between two dependant variables and multiple independent variables of this study; to test various hypotheses for significance (Pallant, 2013, p.146). In this current study, the dependant variables are resistance to change and BI. The remaining variables are all considered

independent. The section below explains the findings of the proposed hypotheses mentioned in chapter 3. The null hypothesis for each research question, as well as the results from the regression analysis, is enlisted below. The results presented are to enable a better understanding of clarity for the reader of this research.

5.7.2.1 TESTING HYPOTHESIS 1

The null and alternative hypotheses for testing clinicians' BI towards EHR adoption and use were as follows:

Null hypothesis 1: Performance expectancy will not have a positive influence on clinicians' behavioural intentions to use the EHR.

Alternate hypothesis 1: Performance expectancy will have a positive influence on clinicians' behavioural intentions to use the EHR.

Multiple regression was used to investigate if PE could predict clinicians' BI towards the EHR. The output of the regression analysis is indicated in Table 19. The correlation coefficient (R) of .778 indicates that RC, PE, SI, and FC are highly correlated with BI. The model explained 60.5% of the variance and was a significant predictor of BI, F (4,117) = 44,836, p< .001).

Table 19

Linear regression analysis for hypotheses 1, 3, 4 and 5

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.778[a]	**0,605**	0,592	0,607

a. Predictors: (Constant), RC, FC, SI, PE

b. Dependent Variable: BI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	66,088	4	16,522	**44,836**	.000[b]
	Residual	43,114	117	0,368		
	Total	109,202	121			

a. Dependent Variable: BehaveInt

b. Predictors: (Constant), RC, FC, SI, PE

Coefficients[a]

Variable	*B	B	t (122)	Sig. (p-value)
(Constant)	1,803		5,924	**0,000**
PE	0,477	0,524	7,181	**0,000**
SI	0,011	0,012	0,182	0,856
FC	0,296	0,317	4,454	**0,000**
RC	-0,092	-0,122	-2,029	**0,045**

a. Dependent Variable: BehaveInt

b. Unstandardized Beta: *B

The subject PE contributed significantly to the model (B = .524, p <0.05). Thus, for every unit increase of PE, BI increased by .524. Therefore, the null hypothesis is rejected. The BI prediction equation, identified as BI = 1.803 + 0.477 PE, is illustrated in Figure 5.

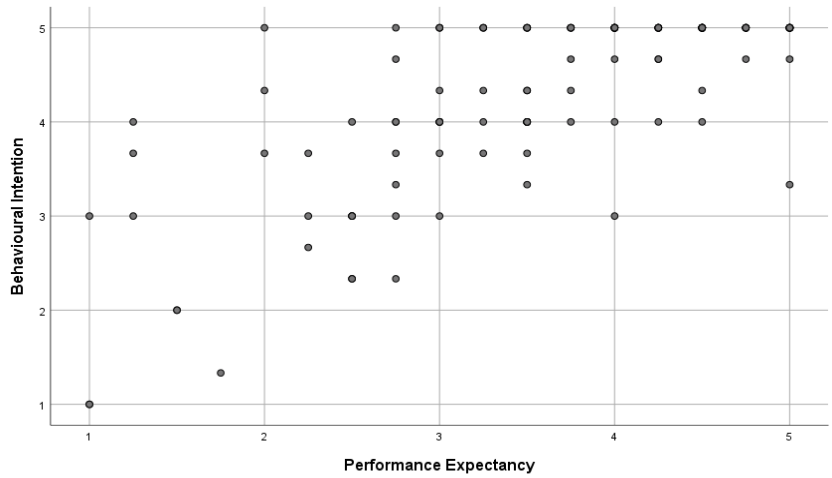

Figure 5: Behavioural Intention vs. Performance Expectancy

5.7.2.2 TESTING HYPOTHESIS 2

Null hypothesis 2: Effort expectancy will not have a positive influence on clinicians' behavioural intentions to use the EHR.

Alternate hypothesis 2: Effort expectancy will have a positive influence on clinicians' behavioural intentions to use the EHR.

Due to the multicollinearity detected in section 5.7.1, the null hypothesis is supported, and the alternate hypothesis rejected as this variable was removed from the remainder of the study. Similarly, the same hypothesis proposed by Hossain et al. (2019) was not supported by their study. Reviewing the results of the factor analysis, EE loaded heavily under the same factor as PE and strongly correlated with both PE and FC. Therefore, it can be assumed that it may have had the same effect as PE on BI if its results were compounded to formulate a new composite variable.

5.7.2.3 TESTING HYPOTHESIS 3

Null hypothesis 3: Social influence will not have a positive influence on clinicians' behavioural intentions to use the EHR.

Alternate hypothesis 3: Social influence will have a positive influence on clinicians' behavioural intentions to use the EHR.

Regression analysis was performed to investigate whether SI could predict clinicians' BIs towards the EHR. The output of the regression analysis is indicated in Table 19.

Furthermore, the subject SI did not contribute to the model significantly (B = .012, p = .86). Thus, for every unit increase of PE, BI increased by .011. Therefore, the null hypothesis is accepted, and the alternate hypothesis rejected. The BI prediction equation, identified as BI = 1.803 + .11 SI, is illustrated in Figure 6.

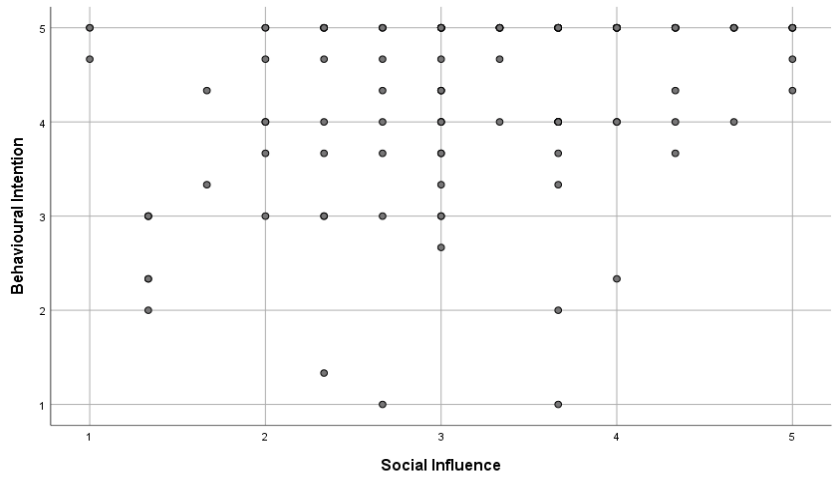

Figure 6: Behavioural Intention vs. Social Influence

5.7.2.4 TESTING HYPOTHESIS 4

Null hypothesis 4: Facilitating conditions will not have a positive influence on clinicians' behavioural intentions to use the EHR.

Alternate hypothesis 4: Facilitating conditions will have a positive influence on clinicians' behavioural intentions to use the EHR.

Regression analysis was performed, to investigate whether FC could predict clinicians' BI towards the EHR. The output of the regression analysis is indicated in Table 19. Furthermore, the subject FC contributed significantly to the model (B = 0.317, p< .05). Thus, for every unit increase of FC, BI increased by .296. Therefore, the null hypothesis is rejected, and the alternate hypothesis accepted. The BI prediction equation, identified as BI = 1.803 + .296 FC, is illustrated in Figure 7.

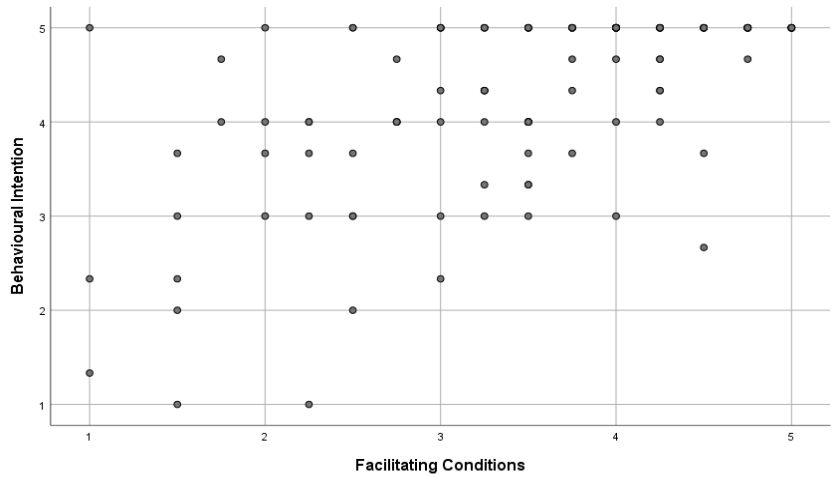

Figure 7: Behavioural Intention vs. Facilitating Conditions

5.7.2.5 TESTING HYPOTHESIS 5

Null hypothesis 5: Resistance to change will have no negative influence on clinicians' behavioural intentions to use the EHR.

Alternate hypothesis 5: Resistance to change will have a negative influence on clinicians' behavioural intentions to use the EHR.

Regression analysis was performed to investigate whether RC could negatively predict clinicians' BI towards the EHR. The output of the regression analysis is indicated in Table 19. Furthermore, the subject resistance to change contributed significantly to the model (B = -.122, p< .05). Thus, for every unit increase of resistance to change, BI decreased by .122. Therefore, the null hypothesis is rejected, and the alternate hypothesis accepted. The BI prediction equation, identified as BI = 1.803 - .092 RC, is illustrated in Figure 8.

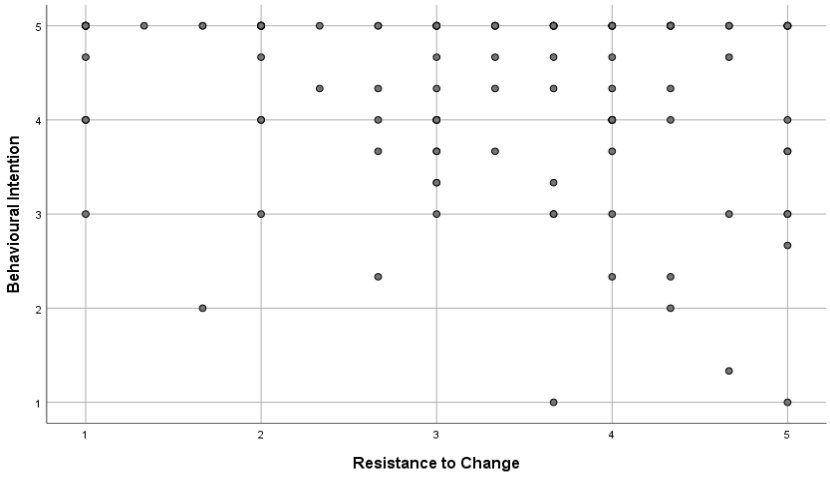

Figure 8: Behavioural Intention vs. Resistance to Change

5.7.2.6 TESTING HYPOTHESIS 6

Null hypothesis 6: A negative attitude towards organisational change will have no influence on clinicians' resistance to change.

Alternate hypothesis 6: A negative attitude towards organisational change will have a positive influence on clinicians' resistance to change.

Regression analysis was performed to investigate whether a negative ATC could predict clinicians' RC. The output of the regression analysis is indicated in Table 20. The correlation coefficient (R) of .287 indicates that attitude to organisational change has a small but significant correlation with RC. The model explained 8.2% of the variance and was a small but significant predictor of BI, F (120,121) = 10,765, p< .01).

Furthermore, the subject attitude towards organisational change contributed significantly to the model (B = .287, p< .05). Thus, for every unit increase in a negative ATC, RC increased by .287. Therefore, the null hypothesis is rejected, and the alternate hypothesis accepted. The BI prediction equation, identified as BI = 2.132 + .473 ATC, is illustrated in Figure 9.

Table 20

Linear regression analysis for hypotheses 6

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.287[a]	0,082	0,075	1,209

a. Predictors: (Constant), ATC

b. Dependent Variable: RC

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15,727	1	15,727	10,765	.001[b]
	Residual	175,309	120	1,461		
	Total	191,036	121			

a. Dependent Variable: RC

b. Predictors: (Constant), ATC

Coefficients[a]

Variable	*B	Std. Error	Beta	t (122)	Sig.(p-value)
(Constant)	2,132	0,324		6,577	**0,000**
ATC	0,473	0,144	0,287	3,281	**0,001**

a. Dependent Variable: RC

b. Unstandardized Beta: *B

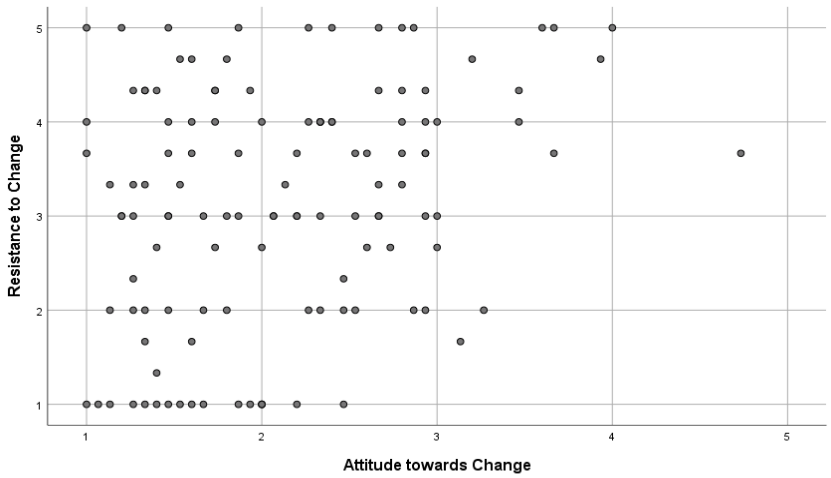

Figure 9: Resistance to Change vs. Attitude towards Organisational Change

5.8 Chapter Summary

Based on the survey respondents of the current study, the findings of this chapter are summarised as follows:

The relationship between the dependant and independent variables were investigated using regression analysis. The overall results indicated that the attitude to organisational change scale was a small but significant predictor of RC, and the UTAUT model a significant predictor of clinicians' BI towards EHR use and adoption. H2 and H3 were not supported by this study, as the relationships between EE and BI and SI and BI were insignificant. A negative relationship exists between RC and BI. PE and FC were found to positively influence clinicians' BI to adopt and use the EHR system. These findings will be discussed in-depth in Chapter 6.

CHAPTER 6: DISCUSSION

6.1. INTRODUCTION

The purpose of this chapter is to draw on the interrelationships between the literature study of Chapter 2 and the results detailed in Chapter 5. This chapter seeks to present the findings against the background of the theory of technology adoption and acceptance and to obtain a better understanding of the contextually-relevant constructs influencing clinicians' intentions to adopt and use the EHR in South Africa, further highlighting the role of RC. This research intends to contribute to the antecedents of BI, which would ultimately deliver an alternative to improving the explanatory power of the UTAUT model.

The chapter starts with a discussion relating to the measurement instrument used to collect responses. Thereafter, the sample of the demographics is detailed to provide the reader with an in-depth view of the profiles of study participants. The discussion then leads into an overview of the results for each construct and the hypotheses justified, followed by a conclusion of the chapter.

6.2 DISCUSSION OF THE RESULTS OF THE MEASUREMENT MODEL

In this study, the researcher surveyed a medical clinician cohort to investigate their intentions towards EHR systems to address the overarching research question: What are the key determinants of the adoption and use of the EHR in the South African context? The primary objective of this research was to obtain further insight into how the adoption and use of technological innovation, such as the EHR, can improve issues concerning the healthcare sector.

Drawing on the early roots of the UTAUT model, Venkatesh et al. (2003) claimed that the use of technology acceptance models to assess user intentions towards technological innovation had been popularised. Similarly, in the current study, the UTAUT was used to assess users' (clinicians') intentions towards EHR adoption in the healthcare system in South Africa. The empirical findings of this study provided further insight into the various constructs of the UTAUT model. A total of six constructs were measured from the original UTAUT model, which include PE, EE, SI, FC and BI, and RC from recently adapted models. Furthermore, this study also provided insights into the behavioural factors, such

as ATC, which contribute towards resistance and influence EHR adoption. The results of this research are relatively consistent with that of the results of earlier research utilising the UTAUT in the field of health informatics.

Six relationships were hypothesised between the variables and these were tested using the data from the survey. Multiple regression analysis was used to assess the measurement model and the model proved to be both valid and reliable. Exploratory factor analysis unveiled the multicollinearity issues of the construct EE. This item was removed from the analysis. Multiple regression analysis revealed that the model predicted 60.5% of the variance of BI towards the adoption of EHR systems. The remaining results are discussed below.

6.3 Sample Demographics

The demographic component of the questionnaire sought to determine the features of the study sample. The participants of this research constituted to 168 clinicians who work within South Africa's health care sector. Only 122 responses were valid for interpretation.

Gender characteristics revealed a predominant male gendered (54.1%) sample in comparison to 49.5% of females. This was anticipated as it is widely known that women clinicians lag their male colleagues. In terms of the age representation, 23.8% of the respondents were older than the age of 55, followed by the 31 to 35 age group (16.4%). This result was not anticipated as the more than 55 age group was the lowest represented age group in multiple previous UTAUT studies (Barrett, 2018; Dasgupta & Gupta, 2019; Hossain et al., 2019).

The majority of the respondents (57%) indicated they were specialists in their field, followed by 43% of respondents who were general practitioners. Almost all respondents (91.8%) had over three years of working experience, and a little over half (53.3%) were regular users of IT systems in healthcare. The majority (89.3%) confirmed voluntariness to use the EHR despite only 27% revealing that they had no current or past experience using the EHR system. This was a surprising finding considering the majority of the sample were older than the age of 55, which is commonly associated with high levels of resistance towards the EHR (Bawack & Kamdjoug, 2018).

The researcher believes that the number of participants who responded to this survey was adequate for this study. No explicit sampling biases within the sample were a reason for

concern. The succeeding sections will clarify the findings for each measured construct and will highlight the key findings of the measurement model.

6.3 Hypothesis 1: Performance Expectancy (PE)

Testing hypothesis 1 was pursuant to fulfilling the second research objective, which was stated as follows: To identify the factors influencing the adoption of the EHR.

6.3.1 RESULTS OF TESTING HYPOTHESIS 1

In the current study, the four test items of PE were adapted from constructs of various technology acceptance, which include: perceived usefulness, extrinsic motivation, job-fit, relative advantage, and outcome expectations (Venkatesh et al., 2003, p. 447). The reliability of the four test items was .853, above the acceptable range. The subject PE was found to have the most significant influence on clinicians' BI towards the EHR. This finding is consistent with the results of previous studies. Hoque and Sorwar (2017) found the PE has a significant effect on influencing the adoption of mHealth. Bawack and Kamdjoug (2018) discovered PE to be a powerful predictor in influencing the adoption of HIS, especially in younger clinicians (<40 years of age). Dasgupta and Gupta (2019) studied the role of PE in a developing country with emerging technology, like South Africa. The results of their study show that PE influences user's usage of the internet. As in the current study, Gajanayake, Iannella and Sahama (2016) confirmed that PE was the most significant predictor of individuals' intentions to use the AeH system.

From the literature review, PE was cited to be the most powerful determinant of BI. This indicates clinicians in this sample believe that usage of the EHR system would provide benefits to improve aspects of their overall job performance. Patient monitoring, disease management and disease control are just some of the benefits achieved from using the technology (Badran, 2019). As the results of this study are in support of hypothesis 1, the objective was thus satisfied.

6.4 Hypothesis 2: Effort Expectancy (EE)

Testing hypothesis 2 - EE will have a positive influence on clinicians' intentions to use the EHR - was pursuant to fulfilling the second research objective, which was stated as follows: To identify the factors influencing the adoption of the EHR

6.4.1 RESULTS OF TESTING HYPOTHESIS 2

The three test items of EE were derived from factors of previous models: perceived ease of use, complexity, and ease of use (Venkatesh et al., 2003, p. 450). The results of this study did not support hypothesis 2. During the assessment of the model, EE was found to have multicollinearity as it was highly associated with the variables PE and FC. The construct was removed from further analysis. This finding was initially surprising as most studies had included EE in their analyses. However, by not having a significant effect on BI, EE supports previous studies investigating the antecedents of BI (Hossain et al., 2019).

Furthermore, this current study found that EE, FC, and PE loaded on the same component demonstrating above normal levels of association between the constructs. There is a possibility that the respondents of this study drew associations between both variables. As illustrated in the literature review, PE refers to the degree of benefit a person believes they will receive through the use of the technology that will improve productivity (Venkatesh et al., 2003); while EE refers to the degree of effort, a person exerts to use new technology (Venkatesh et al., 2003). According to Gajanayake, Iannella and Sahama (2016), both constructs deal with the technological context of a system that relates to "an individual's evaluation of the system" (p.221). Venkatesh et al. (2003) explained that questions concerning FC – a construct related to supporting resources and infrastructure – are covered extensively by the EE variable, which relates to the degree of ease an individual uses technology. The authors further added that when EE is removed from the measurement model, FC would, in its place, predict users' BI.

Furthermore, Venkatesh and Morris (2000) proposed, based on previous scholarship, that the construct EE is a better predictor of BI in females than in males and would be more significant in older women with very little usage experience with the technology. This finding could be a reason as to the failure to prove the second hypothesis as the majority of participants in this study were older males.

6.5 Hypothesis 3: Social Influence (SI)

Testing hypothesis 3 was pursuant to fulfilling the second research objective, which was stated as follows: To identify the factors influencing the adoption of the EHR.

6.5.1 RESULTS OF TESTING HYPOTHESIS 3

The three test items of SI were derived from the following model constructs: subjective norm, social factors, and image (Venkatesh et al., 2003, p. 451). SI did not influence clinicians' intentions of adopting the EHR. With no proven effect on BI, SI contradicts previous studies investigating the BI of clinicians towards technology adoption and use (Hoque & Sorwar, 2017; Hossain et al., 2019; Venkatesh et al., 2003). This was a surprising finding as clinicians may often refine their intentions based on information that other clinicians have adopted a technological system (Hossain et al., 2019).

Humans are social beings, and their propensity to carry out a particular behaviour under SI is explored by the theory of diffusion of innovation (Rogers, 1995), as alluded to in chapter 2. The author describes diffusion as the process of individuals of a social network communicating an innovation over time. The theory explains that adoption of technology occurs through a series of stages which include understanding, persuasion, decision, implementation, and confirmation (Rogers, 1995. This emphasises the importance of SI on technology adoption. Venkatesh et al. (2003) posit that where the use of technology is obligatory, SI's relevance only becomes apparent in the earliest phases of an individual's interaction with the technology and slowly erodes over time, later becoming almost insignificant. However, in voluntary settings, SI's role is found in an individual's opinion of the system.

This raises the question as to whether adequate social support exists to positively influence the clinicians of this study to adopt the EHR system within their organisations, or whether they devalue SI when adopting or using technology over time.

6.6 Hypothesis 4: Facilitating Conditions (FC)

Testing hypothesis 4 was pursuant to fulfilling the second research objective, which was stated as follows: To identify the factors influencing the adoption of the EHR.

6.6.1 RESULTS OF TESTING HYPOTHESIS 4

The four test items of FC were derived from the following model constructs: perceived behavioural control, FC, and compatibility (Venkatesh et al., 2003, p. 453). FC was found to have a significant influence on clinicians' BI to use the EHR system. This is not apparently surprising as eHealth infrastructure, adequate training in new technology, competent ICT trained human resources, and technical sufficiency is critical success factors that support the development of clinicians' positive attitude towards the EHR (Hossain et al., 2019). These factors are instrumental in clinicians' adoption of the system. Furthermore, the advancement of EHR adoption is dependent on IT infrastructure (Bhattacherjee & Hikmet, 2008). Lee, Y.T. Park, J.S. Park, & Yi, (2018) verified that the complete adoption of the EHR was positively associated with technological infrastructure in healthcare facilities. The authors added that policies that support IT infrastructure was fundamental to the fast rollout of EHR systems.

6.7 Hypothesis 5: Resistance to Change (RC)

Testing hypothesis 5 was pursuant to fulfilling the third research objective, which was stated as follows: To fill in the gap in literature regarding the role of RC in EHR adoption in South Africa.

6.7.1 RESULTS OF TESTING HYPOTHESIS 5

To keep up with the rapid economic, technological and geopolitical changes, companies are increasingly required to develop and enforce change processes (Oreg, 2017). As such, resistance toward change is often seen as a barrier to effect change. Three test items of RC were derived from previous studies (Hossain et al., 2019). It was expected that RC would be found to be negatively associated with BI, given that it is identified as a

barrier to EHR adoption. When it comes to new technology implementation and use, clinicians are recognised as the most critical stakeholders in the healthcare industry (Safi et al., 2018). Barrett (2013) found that clinicians with more work experience are the most resistant to organisational change. The reason being, using the underpinnings of the job characteristics model (JCM), is that EHR implementation affects workplace autonomy (Barrett, 2018). Hoque and Sorwar (2017) found a negative but significant relationship between RC and BI to adopt mHealth services. The authors proposed that elderly individuals show higher levels of resistance due to their lack of technological skills and technology anxiety. As 23.8% of this study's population was older than age 55, the age of participants likely supported the findings. Bhattacherjee and Hikmet (2008) found that resistance negatively impacted BI. The authors added that physician resistance occurred as a result of the perceived threat of the CPOE (Computerised Physician Order Entry) system with the fear that they would lose control over their workflows. The study concluded that resistance was a serious impediment to the sustainable success of the EHR system (Bhattacherjee & Hikmet, 2008).

6.8 Attitude Towards Organisational Change (ATC)

Testing hypothesis 5 was pursuant to fulfilling the third research objective, which was stated as follows: To fill in the gap in literature regarding the role of RC in EHR adoption in South Africa.

6.7.1 RESULTS OF TESTING HYPOTHESIS 6

In this study, a negative ATC had a significant but small impact on clinicians' resistance. Gajanayake, Ianella and Sahama (2016) confirmed that attitude – "an individual's overall affective reaction to using ICT" (p.221) – had a direct effect on BI and age was a significant moderator of respondents' attitudes. Oreg (2003) proposed a tri-dimensional approach to understanding RC using the change attitude scale, as such a view encapsulates the complexity behind resistance. The author's study confirmed the tri-dimensional model of resistance. A large part of technology consists of the interest and emotions of an individual in the pleasure and enjoyment felt when using ICT. Therefore, an individual's motivation and performance is influenced by their attitude (Gajanayake et al., 2016).

6.9 Clinicians' Intentions towards Future EHR use

The frequency of the responses for the model items was sorted based on their means, as illustrated in Figure 4. The behavioural items (B1, B2 and B4) of the Change Attitude Scale – items involving "both behaviours and intention to behave" – were negatively responded to by the majority of the respondents (M = 1.66, SD = 1.027) (Oreg, 2006, p. 83). In contrast, the BI items were positively responded to. Despite clinicians' resistance, they remain optimistic about the technological abilities of the EHR to support their work performance in healthcare settings.

As most respondents (83%) indicated their voluntariness to use the EHR, this positive finding implies that a large portion of clinicians in South Africa will welcome the EHR when implemented across their health facilities in the future. Furthermore, 73% of clinicians in this study reportedly have past or current experience using the EHR. This is surprising since many previous articles cited low adoption rates amongst clinicians (Hossain et al., 2019). This finding may reflect that a large proportion of this study's participants were based in technically sufficient healthcare facilities as opposed to healthcare clinicians based in rural areas. Therefore, this finding may not be indicative of all clinicians in South Africa as clinicians in public and rural care facilities often face inequities, such as poor technical infrastructure (Winchester & King, 2018).

6.10 Conclusion

In light of the findings of this research, Figure 10 illustrates the relationships that were identified based on the respondents of the survey. The diagram also indicates the core literature supporting the relationships identified in this study. In addition to satisfying the objectives of this research in predicting clinicians' intentions toward BI, relationships between other variables have provided a better understanding of the UTAUT model, which is subdivided into technological, environmental, and individual factors which were guided by previous literature. The relationships between other variables are as follows: the association between EE and PE and EE and FC. As stated in the above sections, EE was excluded from this study and is not illustrated under 'technological factors' in the figure below.

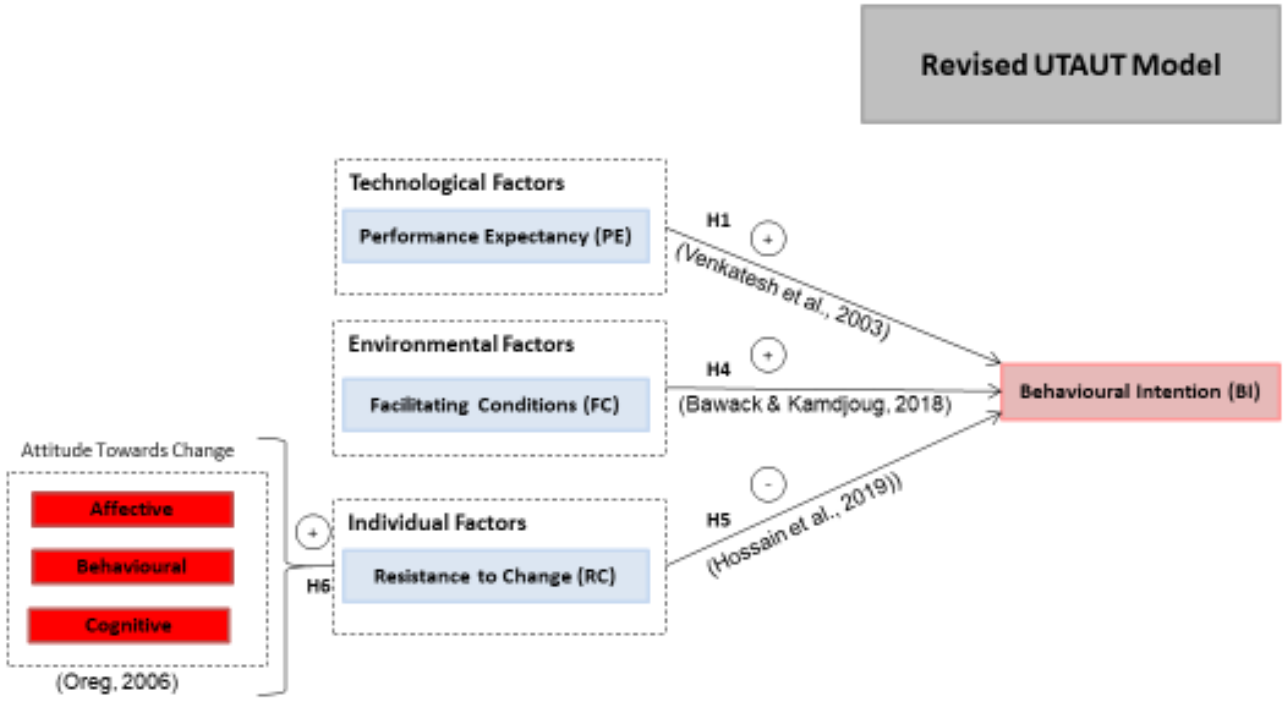

Figure 10: Summarised research findings including supporting literature

The succeeding chapter concludes this research by referring the findings to their purpose and motivation, followed by a discussion offering advice for future research.

CHAPTER 7: CONCLUSION

7.1 INTRODUCTION

This research sought to understand the key determinants of the adoption and use of healthcare technology in South Africa, centring on the EHR.

Despite the successful transition from apartheid into democracy, South Africa continues to grapple with issues of transformation and solving inequities between the private and public health systems (Coovadia, Jewkes, Barron, Sanders, & McIntyre, 2009). Moreover, an ageing populace and a significant burden of communicable diseases, for example, HIV/AIDS and TB, contribute to an unwanted rise in healthcare expenditure (Ahlan & Ahmad, 2014; Coovadia et al., 2009). The implementation of policies, such as the NHI, combined with technological innovation, such as the EHR system, serves to promote health equity, enhance the quality of health services and reduce the total operational costs of healthcare. Globally, however, the low rates of technology adoption, as well as the documented pessimism among clinicians, is a major risk factor for efforts geared towards the sustainable improvement of healthcare systems.

Using an adapted UTAUT model, the factors influencing clinicians' intentions towards EHR adoption and use in the healthcare system were investigated. Determining clinicians' intentions towards the EHR is a critical area of healthcare industry research in emerging economies, similar to South Africa, plagued by issues of inadequate access to healthcare services and insufficient resources. Furthermore, for the NHI to work effectively, the scheme has to be able to register and monitor patients – a core function of the EHR (Katurura & Cilliers, 2018). As clinicians are the key deciding stakeholders within the healthcare community who utilise and promote digital health technology, their cooperation in EHR adoption and implementation would support the advancement of healthcare industries worldwide (Ayanso et al., 2015).

7.2 PRINCIPAL FINDINGS

The purpose of this study was to contribute to the understanding of clinicians' behavioural intentions towards the EHR through the fulfilment of the following objectives:

1. Obtain further insight into how the adoption and utilisation of the EHR can lead to improvements in healthcare.
2. Determine the factors that play a key role in EHR adoption.
3. To address the gap in literature regarding the role of RC in EHR adoption in South Africa.

The research question - what are the key determinants of the adoption and use of healthcare technology in the South African context? - led to the development of the objectives of this study, highlighted above. As noted in Chapter 2, although there had been a surge in literature and research relating to technology adoption worldwide, evidence in understanding the factors influencing the adoption of the EHR and the role of resistance in a developing setting is lacking. Therefore, literature in the UTAUT field led to the development of the current study's hypotheses recaptured below:

- Hypothesis 1: PE will have a positive influence on clinicians' BI to use the EHR.
- Hypothesis 2: EE will have a positive influence on clinicians' BI to use the HER.
- Hypothesis 3: SI will have a positive influence on clinicians' BI to use the EHR.
- Hypothesis 4: FC will have a positive influence on clinicians' BI to use the EHR.
- Hypothesis 5: RC will have a negative influence on clinicians' BI to use the EHR.
- Hypothesis 6: A negative ATC will have a positive influence on RC.

With the digitisation of the healthcare industry, the present research is a major contributor to EHR healthcare system research in an emerging country like South Africa. Concerning the theoretical viewpoint, this research underscores the relevance of attitudinal influences on clinicians' intentions towards the EHR. While some healthcare professionals are utilising various forms of technology in their practices, more urgency is required to increase adoption and use of HIT to improve health care outcomes in South Africa. As a result, exciting findings related to the survey respondents are highlighted below.

7.2.1 PRINCIPAL FINDINGS OF HYPOTHESIS 1, 3 AND 4

In the current study, PE and FC had the most significant effect on clinicians' intentions towards EHR adoption and use. Therefore, the technological features of the EHR improving job performance and the organisational support and technical resources available to support the EHR system, are the most important drivers of the adoption and

future use of the EHR. This is reiterated by Philips (2019) in the 'Future Health Index Country Report' – a forum that helps to identify countries' readiness to attend to health issues and develop sustainable health care systems. The report found that the major drivers of digital health technology use were clear benefits (return on investment) received and easy sharing across devices and between patients.

Furthermore, the technical infrastructure is considered a critical support factor in the successful implementation of the EHR (Katurura & Cilliers, 2016). Many healthcare facilities in South Africa do not have the necessary IT infrastructure or the support of IT skilled staff to adopt or use the EHR. A compounding factor is South Africa's low adoption rate of digital health records (DHRs), which lags the 15-country average (Philips, 2019).

Social and personal forces, as described in Chapter 2, shape the way clinicians adopt and use the EHR system (Katurura & Cilliers, 2016). No significant co-relationship was found between SI and BI. The findings of insignificance would suggest that clinicians in this study, which comprised mostly of specialists (57%), were not influenced or directly persuaded by their colleagues or individuals of importance to alter their EHR use behaviour. In line with the psychological needs of Self-Determination Theory, the study by van der Burgt et al. (2019) discovered that autonomy is strongly related to the autonomous motivation for the work of medical specialists. The EHR may affect workplace autonomy, and clinicians with high levels of autonomy often have negative attitudes and resist organisational change (Adenuga et al., 2017; Barrett, 2018). In addition, it is likely that the influence of society - internal social pressure from colleagues or support from management - did not play a role in clinicians' EHR use or behaviour. Although not proven in the current study, the influence of other clinicians is an authoritative referent power on other clinicians to conform to EHR use (Venkatesh et al., 2003). This could provide an indication of the prevalence of societal change occurring at the individual, society, and community levels in South Africa.

7.2.2 PRINCIPAL FINDINGS OF HYPOTHESES 5 AND 6

This study is not the first to postulate that clinicians are the most critical stakeholders to ensure the success of new technology adoption and implementation (Ayanso et al., 2015). This study is also not the first to argue that the use of the EHR system is dependent on clinicians' openness towards organisational change and employment cultures (Barrett,

2018; Hossain et al., 2019; Oreg, 2003; Oreg, 2006). Clinicians have been depicted as mostly accepting of the idea of the EHR due to its many benefits but are often unhappy with its practical use.

South African clinicians are not making full use of technology as it is reported that almost two-thirds of clinicians do not utilise artificial intelligence (AI) technology in their daily routines (Philips, 2019). As stated in Chapter 2, low technology adoption and use of the EHR can be explained by barriers such as its time-consuming attributes, high initial implementation and data costs, security concerns, legal and regulatory implications, contributions to physician burnout, and interference with patient communication. In addition, due to the practical nature of a clinician's work, the EHR poses risks that threaten workflow autonomy (Barrett, 2018).

In this present study, resistance was conceptualised by a tri-dimensional model of attitude. The three dimensions: affective, behaviour and cognitive, made a significant contribution towards clinicians' resistance to the EHR system. Attitude plays a critical role in users' adoption and use of technology (Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019). Individuals may also use a new technology based on the degree of their attitude despite them consciously intending to use the technology (Dwivedi et al., 2019). This study found that a negative attitude played a small but significant role in adopting the EHR. The focus of this construct was clinicians' personality and its implications on EHR adoption. This implies that clinicians' negative attitude towards the EHR further explained their resistance towards the technology, which then negatively influenced their intentions towards adopting the EHR.

The present study also found a surprisingly significant negative relationship between RC and clinicians' BI towards EHR adoption and use. This finding contradicted the previous work of Hossain et al. (2019), who found no significant link between RC and clinicians' BI towards the EHR. The reasons postulated by the authors is that the majority of their sample consisted of young physicians (between ages 25 and 40). A large majority of the participants of the current study were older than age 55. As indicated in the previous section, older clinicians may feel resistance to new technology as opposed to younger clinicians. The findings suggest that despite the many benefits of the EHR in reducing costs, improving efficiency, and patient outcomes, clinicians demonstrate resistance towards the EHR. Many clinicians, especially those older than the age of 40, have technology anxiety and revert to using traditional healthcare methods such as the paper-

based system (Hoque & Sorwar, 2017). From a cultural lens, the EHR and the concept of mutual data sharing are relatively new in South Africa, where only one in five healthcare professionals encourage the use of health information technology to their patients (Philips, 2019).

Resistance, in this context, is further increased by the fear of increased administrative costs associated with the EHR and its contribution to physician burnout (Jha et al., 2019). Inadequate human resource capacity adds an additional layer of complexity to the already complex healthcare system. Clinicians are often outnumbered by their patients and find it challenging to meet the demands of high patient volumes (Scott & Mars, 2015). Furthermore, introducing a complex process – like the EHR system - into a highly demanding health care setting may be negatively perceived by clinicians (Mishuris & Linder, 2013).

The methodologies employed in the present study are sufficient to conclude that RC is an inhibitor of clinicians' intentions to adopt and use the EHR. These results are imperative since they underline the importance of utilising individual characteristics when re-modelling existing IT theories in research.

7.2.3 ALIGNMENT WITH THE PURPOSE OF THE STUDY

This research was conducted using quantitative techniques by investigating the influences on clinicians' intentions towards the EHR. This study made the following contributions to the body of knowledge:

(a) Unwraps the link between ATC and RC, operationalises RC and illustrates it as a conduit between ATC and BI;
(b) Dovetails together three pillars of technology adoption in health care: the technological features of the EHR as perceived by PE and EE; the social and environmental factors (SI and FC) which facilitate clinicians' adoption and use of the EHR, and; individual factors (ATC and RC) which emphasize the role of a clinician's character in the adoption and use of technology.

Finally, the expansion of the original UTAUT model to incorporate the interplay between individual factors and BI was used to predict clinicians' intentions towards the EHR in the South African context. H1 to H5 explained 60.5% of the variance of clinicians' intentions to adopt the EHR, whereas H6 explained 8.2% of the variance of clinicians' RC, all of

which is a significant expansion of the understanding of clinicians'' use of the EHR in healthcare organisations.

7.3 Implications For Management

Chapter 1 detailed the relevance of this study for healthcare administrators and EHR vendors as the successful implementation of health technologies is dependent on key stakeholders' acceptance (Safi et al., 2018). In the academic context, it was predicted that underlining the factors influencing clinicians' intentions toward the EHR would be beneficial. In the business context, the insights gained from this research may provide valuable information to policymakers and EHR vendors to better adapt the EHR to fulfil the requirements of the users of the technology in order to increase adoption rates. This research also served to inform current or future entrepreneurs who aspire to establish EHR platforms or to direct strategies for adoption. The sub-sections below will illustrate the implications of this research for applicable stakeholders.

7.3.1 Implications and Recommendations for South African Healthcare Facilities

This study set out to enhance the understanding of the antecedents influencing clinicians' adoption of the EHR in South Africa. By understanding the many barriers to HIT use could help improve the working lives of clinicians and patient health outcomes. This study examined the basic UTAUT with added constructs, ATC and RC, to better explain clinicians' resistance towards the EHR. The extended variable ATC had a small but significant impact on RC, whereas RC negatively influences clinicians' BI. The proposed model of this study will, therefore, define the degree of clinician resistance when using the EHR and may be applied to industries where individuals are resistant to welcoming novel digital health technologies.

This study's empirical findings may further provide valuable information concerning the design and establishment of realistic context-relevant guidelines to ensure the successful implementation of the EHR system in South Africa. The lessons from the U.S. experience, as detailed in Chapter 2, highlight the importance of the government's role in forging a future policy framework (e.g., HITECH Act) and setting criteria (Meaningful Use) to be met. Frameworks and guidelines should be standardised but suited to the challenges unique to South Africa. This should also be done through a consultative process where key

stakeholders from both the private and public health sectors can engage in open dialogue. Ensuring all health care providers operate from the same standard framework would assist with the interoperability issues between various EHR systems. Furthermore, the implementation of new digital technology (such as the EHR) in complex hospital settings necessitates a well-planned strategy. Establishing professional bodies dedicated solely to the development of frameworks would possibly solve the lack of precision in digital health strategies on the African continent (Achampong, 2012).

Furthermore, the implementation of policy should be focussed on younger clinicians. As technology continues to advance in healthcare, especially in the training of medical students, clinicians can be prepared for the digital future of medicine by integrating telemedicine or EHR in the context of medical school learning programmes. Where young students and junior practitioners are exposed to HIT at an earlier stage, the levels of resistance will ideally be lowered in the future and the technology gap contracted.

As detailed in Chapter 6, the constructs PE and FC are the most powerful predictors of clinicians' BI towards EHR adoption and use. This offers evidence to policymakers and administrators to invest in ICT skilled staff, training programmes and infrastructure sufficiency. Through the improvement of the technical climate, clinicians will be more inclined to adopt and utilise EHR systems. Considering the high initial implementation and maintenance costs (such as data costs) associated with the EHR, adequate funding or reimbursement by tax incentives (as done in the U.S.) should be carefully considered as this is documented as one of the major barriers to EHR adoption.

In the current study, while SI was insignificant to EHR adoption by clinicians, policymakers and healthcare administrators should not neglect the importance of social councils in sharing best use practices and electing ambassadors who are able to champion the EHR system through the creation of positive SI.

Implementing the EHR on the African continent has been a challenge since many hurdles exist, which impede the adoption and use of the technology. Governments must assume the role of setting societal norms that define the knowledge environment, where the communities are technology, legal, policy and consumption (Gajanayake et al., 2016).

7.6 LIMITATIONS

Several limitations of this study should be noted. The design of this study followed a cross-sectional approach via purposive sampling, as stipulated in Chapter 4. The cross-sectional design may not be a clear representation of the impact on the use of technology. Furthermore, the sampling method chosen for this study denotes that the results cannot be translated as true for the entire population (Saunders & Lewis, 2018). To mitigate this, prior researchers have suggested undertaking longitudinal studies to clarify the impact of clinicians' intentions towards technology fully.

This study was based on the UTAUT model to determine the antecedents to clinicians' BI towards the EHR. The UTAUT model may be seen as inadequate in completely predicting HIS adoption within a developing context where issues of complexity prevail (Hossain et al., 2019). However, literature has also stressed the need for the replicability of this type of research throughout Sub-Saharan Africa utilising context-specific features as moderators of the UTAUT model to increase its explanatory power (Bawack & Kamdjoug, 2018).

This study was not extended to other key stakeholders in the adoption and use of the EHR, such as nurses and patients. Investigating their intentions towards the EHR may be impactful in providing policymakers and EHR vendors with a holistic view of the intentions towards the technology, which will aid in adapting features of the system to the needs of key stakeholders.

Lastly, due to the time constraints of this research, a sample size in keeping with that of previous research (above 250 respondents) would allow the researcher to perform statistical analyses such as structural equation modelling (SEM), the preferred statistical method in previous studies, to draw direct comparisons to results of previous scholars in the field of UTAUT.

7.7 Recommendations for Future research

The following section offers recommendations for future research.

- The current study excluded moderators of the existing UTAUT model (such as age, gender, experience and voluntariness of use), as the focus of this research was the behavioural processes associated with technology adoption and use. Previous studies, such as by Hossain et al. (2019), identified that moderating factors had a profound influence on clinicians' BI towards the EHR. Future researchers may find value in incorporating moderating factors into the adapted UTAUT model to improve the explanatory power of clinician resistance.

- Developing countries experience different challenges in healthcare than in developed economies. As the EHR system is a relatively new concept in developing settings, adapting the UTAUT model or utilising context-relevant constructs to better explain resistance may provide a more generalised depiction of resistance.
- There are three important pillars in the healthcare industry: patients (the consumers of care), clinicians (the providers of care/consumers of digital technology), and provider organisations (Beglaryan et al., 2017). Investigating their intentions towards the EHR in a single study may provide a deeper understanding of EHR acceptance in a developing context. Furthermore, as there is a paucity of knowledge in EHR adoption in developing countries, further research in the field is required to develop a framework that may assist healthcare industries on the African continent.

7.8 Concluding Remarks

This study contributes to UTAUT research in healthcare, which in an emerging environment such as South Africa, necessitated future scholars to investigate the antecedents of the BI of clinicians towards the EHR programme.

Clinicians are the primary service providers of healthcare, the primary consumers digital health technology (such as the EHR), and the key stakeholders in the promotion and use of the EHR. Therefore, their adoption of HIT has the potential of enhancing the quality of healthcare service delivery and improving patient outcomes worldwide. Healthcare is a fundamental human right that intersects all distinctions of age, gender, ethnicity, culture and geographical location. The healthcare industry is a huge area of concern for both developed and developing economies; therefore, applications such as the EHR may assist reforms in improving the current global healthcare situation. For the future application of UTAUT field research, adjusting the framework to include contextually relevant predictors to better understand HIT adoption in an emerging market is advised.

The empirical results of this study established PE, FC, and RC as the most important predictors of clinicians' intentions towards the EHR system and ATC, a small but significant antecedent of RC. Whereas EE and SI had no effect in this regard. The results of this research offer valuable information for clinicians, strategists, policymakers, and developers to establish policies to orchestrate the successful implementation of the EHR system in South Africa.

REFERENCES

Achampong, E. K. (2012). Electronic health record system: a survey in Ghanaian hospitals. *Journal of Health & Medical Informatics*, *03*(02). https://doi.org/10.4172/scientificreports.164

Adenuga, K. I., Iahad, N. A., & Miskon, S. (2017). Towards reinforcing telemedicine adoption amongst clinicians in Nigeria. *International Journal of Medical Informatics*, *104*, 84–96. https://doi.org/10.1016/j.ijmedinf.2017.05.008

Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *Journal of Health Economics*, *34*, 19–30. https://doi.org/10.1016/j.jhealeco.2013.12.005

Ahlan, A. R., & Ahmad, B. I. (2014). User acceptance of health information technology (HIT) in developing countries: a conceptual model. *Procedia Technology*, *16*, 1287–1296. https://doi.org/10.1016/j.protcy.2014.10.145

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, *50*(2), 179–211.

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

Ayanso, A., Herath, T. C., & O'Brien, N. (2015). Understanding continuance intentions of physicians with electronic medical records (EMR): an expectancy-confirmation perspective. *Decision Support Systems*, *77*, 112–122. https://doi.org/10.1016/j.dss.2015.06.003

Badran, M. F. (2019). eHealth in Egypt: the demand-side perspective of implementing electronic health records. *Telecommunications Policy*, *43*(6), 576–594. https://doi.org/10.1016/j.telpol.2019.01.003

Bamford, L. J., McKerrow, N. H., Barron, P., & Aung, Y. (2018). Child mortality in South Africa: fewer deaths, but better data are needed. *South African Medical Journal*, *108*(3), 25–32.

Barrett, A. K. (2018). Electronic health record (EHR) organizational change: explaining resistance through profession, organizational experience, and EHR communication quality. *Health Communication*, *33*(4), 496–506. https://doi.org/10.1080/10410236.2016.1278506

Bawack, R. E., & Kamdjoug, J. R. K. (2018). Adequacy of UTAUT in clinician adoption of health information systems in developing countries: the case of Cameroon. *International Journal of Medical Informatics*, *109*, 15–22.

Beglaryan, M., Petrosyan, V., & Bunker, E. (2017). Development of a tripolar model of technology acceptance: hospital-based physicians' perspective on EHR. *International Journal of Medical Informatics*, *102*, 50–61. https://doi.org/10.1016/j.ijmedinf.2017.02.013

Bhattacherjee, A., & Hikmet, N. (2008). Reconceptualizing organizational support and Its effect on information technology usage: evidence from the health care sector. *The Journal of Computer Information Systems; Stillwater*, *48*(4), 69–76. http://search.proquest.com/docview/232573695/abstract/50D0679E78F04CAAPQ/1

Brenner, S. K., Kaushal, R., Grinspan, Z., Joyce, C., Kim, I., Allard, R. J., Delgado, D., & Abramson, E. L. (2016). Effects of health information technology on patient outcomes: a systematic review. *Journal of the American Medical Informatics Association*, *23*(5), 1016–1036. https://doi.org/10.1093/jamia/ocv138

Bryman, A., & Bell, E. (2014). *Research methodology: business and management Contexts.* Oxford University Press Southern Africa.

Chen, P.-T., Lin, C.-L., & Wu, W.-N. (2020). Big data management in healthcare: adoption challenges and implications. *International Journal of Information Management*, 102078. https://doi.org/10.1016/j.ijinfomgt.2020.102078

Cline, G. B., & Luiz, J. M. (2013). Information technology systems in public sector health facilities in developing countries: the case of South Africa. *BMC Medical Informatics and Decision Making*, *13*, 13–13. PubMed. https://doi.org/10.1186/1472-6947-13-13

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic press.

Coovadia, H., Jewkes, R., Barron, P., Sanders, D., & McIntyre, D. (2009). The health and health system of South Africa: historical roots of current public health challenges. *The Lancet*, *374*(9692), 817-834.

Creswell, J. W. (2006). *Design: qualitative, quantitative, and mixed method approaches*.

Deloitte. (2019). *2019 Global health care outlook: Shaping the future*.

Dasgupta, S., & Gupta, B. (2019). Espoused organizational culture values as antecedents of internet technology adoption in an emerging economy. *Information & Management*, *56*(6), 103142. https://doi.org/10.1016/j.im.2019.01.004

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace 1. *Journal of Applied Social Psychology*, *22*(14), 1111–1132.

Dranove, D., Forman, C., Goldfarb, A., & Greenstein, S. (2012). The trillion dollar conundrum: Complementarities and health information technology. *American Economic Journal: Economic Policy*, *6(4), 239-70*. https://doi.org/10.1257/pol.6.4.239

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Field, A. (2013). *Discovering Statistics Using IBM SPSS Statistics*. SAGE.

Fishbein, M., & Ajzen, I. (1977). *Belief, attitude, intention, and behavior: an introduction to theory and research*.

Gajanayake, R., Iannella, R., & Sahama, T. (2016). An insight into the adoption of accountable-ehealth systems – an empirical research model based on the australian context. *IRBM*, *37*(4), 219–231. https://doi.org/10.1016/j.irbm.2016.01.002

Haried, P., Claybaugh, C., & Dai, H. (2019). Evaluation of health information systems research in information systems research: a meta-analysis. *Health Informatics Journal*, *25*(1), 186–202.

Heart, T., Ben-Assuli, O., & Shabtai, I. (2017). A review of PHR, EMR and EHR integration: a more personalized healthcare and public health policy. *Health Policy and Technology*, *6*(1), 20–25. https://doi.org/10.1016/j.hlpt.2016.08.002

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., & Taylor, R. (2005). Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health Affairs*, *24*(5), 1103–1117. https://doi.org/10.1377/hlthaff.24.5.1103

Holroyd-Leduc, J. M., Lorenzetti, D., Straus, S. E., Sykes, L., & Quan, H. (2011). The impact of the electronic medical record on structure, process, and outcomes within primary care: a systematic review of the evidence: Figure 1. *Journal of the American Medical Informatics Association*, *18*(6), 732–737. https://doi.org/10.1136/amiajnl-2010-000019

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: an extension of the UTAUT model. *International Journal of Medical Informatics*, *101*, 75–84. https://doi.org/10.1016/j.ijmedinf.2017.02.002

Ho, R. (2006). *Handbook of univariate and multivariate data analysis and intepretation with SPSS.* CRC Press.

Hossain, A., Quaresma, R., & Rahman, H. (2019). Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: an empirical study. *International Journal of Information Management*, *44*, 76–87. https://doi.org/10.1016/j.ijinfomgt.2018.09.016

Hsu, C.-L., Lee, M.-R., & Su, C.-H. (2013). The role of privacy protection in healthcare information systems adoption. *Journal of Medical Systems*, *37*(5), 9966. https://doi.org/10.1007/s10916-013-9966-z

Jakovljevic, M., Timofeyev, Y., Ekkert, N. V., Fedorova, J. V., Skvirskaya, G., Bolevich, S., & Reshetnikov, V. A. (2019). The impact of health expenditures on public health in BRICS nations. *Journal of Sport and Health Science*, *8*(6), 516.

Jha, A. K., Iliff, A. R., Chaoui, A. A., Defossez, S., Bombaugh, M. C., & Miller, Y. R. (2019). A crisis in health care: a call to action on physician burnout. *Waltham, MA:*

Massachusetts Medical Society MHaHA, Harvard TH Chan School of Public Health, and Harvard Global Health Institute.

Kandeh, A. T., Botha, R. A., & Futcher, L. A. (2018). Enforcement of the protection of personal information (POPI) act: perspective of data management professionals. *SA Journal of Information Management*, *20*(1). https://doi.org/10.4102/sajim.v20i1.917

Kannampallil, T. G., Schauer, G. F., Cohen, T., & Patel, V. L. (2011). Considering complexity in healthcare systems. *Journal of Biomedical Informatics*, *44*(6), 943–947. https://doi.org/10.1016/j.jbi.2011.06.006

Katurura, M. C., & Cilliers, L. (2018). Electronic health record system in the public health care sector of South Africa: a systematic literature review. *African Journal of Primary Health Care & Family Medicine*, *10*(1). https://doi.org/10.4102/phcfm.v10i1.1746

Katurura, M., & Cilliers, L. (2016). The extent to which the POPI act makes provision for patient privacy in mobile personal health record systems. *2016 IST-Africa Week Conference*, 1–8. https://doi.org/10.1109/ISTAFRICA.2016.7530595

Kim, S., Lee, K.-H., Hwang, H., & Yoo, S. (2016). Analysis of the factors influencing healthcare professionals' adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital. *BMC Medical Informatics and Decision Making*, *16*. https://doi.org/10.1186/s12911-016-0249-8

Krech, R., Kickbusch, I., Franz, C., & Wells, N. (2018). Banking for health: the role of financial sector actors in investing in global health. *BMJ Global Health*, *3*(Suppl 1), e000597. https://doi.org/10.1136/bmjgh-2017-000597

Kruse, C. S., & Beane, A. (2018). Health information technology continues to show positive effect on medical outcomes: systematic review. *Journal of Medical Internet Research*, *20*(2), e41. https://doi.org/10.2196/jmir.8793

Lee, Y.-T., Park, Y.-T., Park, J.-S., & Yi, B.-K. (2018). Association between electronic medical record system adoption and healthcare information technology infrastructure. *Healthcare Informatics Research*, *24*(4), 327–334.

Lewis, M. (2015). Financing global health-trends and directions. *Presentation prepared for consortium of universities for global health*.

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

Marten, R., McIntyre, D., Travassos, C., Shishkin, S., Longde, W., Reddy, S., & Vega, J. (2014). An assessment of progress towards universal health coverage in Brazil, Russia, India, China, and South Africa (BRICS). *The Lancet*, *384*(9960), 2164–2171. https://doi.org/10.1016/S0140-6736(14)60075-1

Mishuris, R. G., & Linder, J. A. (2013). Electronic health records and the increasing complexity of medical practice: “it never gets easier, you just go faster”. *Journal of General Internal Medicine*, *28*(4), 490–492. https://doi.org/10.1007/s11606-012-2304-1

Naledi, Barron, P., & Schneider, T. (2011). Primary health care in SA since 1994 and implications of the new vision for PHC re-engineering. *South African health review* 2011, no. 1 (2011):17-28.

Neely, A. H., & Ponshunmugam, A. (2019). A qualitative approach to examining health care access in rural South Africa. *Social Science & Medicine*, *230*, 214–221. https://doi.org/10.1016/j.socscimed.2019.04.025

Ohuabunwa, E. C., Sun, J., Jean Jubanyik, K., & Wallis, L. A. (2016). Electronic medical records in low to middle income countries: the case of Khayelitsha hospital, South Africa. *African Journal of Emergency Medicine*, *6*(1), 38–43. https://doi.org/10.1016/j.afjem.2015.06.003

Oreg, S. (2003). Resistance to change: developing an individual differences measure. *Journal of Applied Psychology*, *88*(4), 680–693. https://doi.org/10.1037/0021-9010.88.4.680

Oreg, S. (2006). Personality, context, and resistance to organizational change. *European Journal of Work and Organizational Psychology*, *15*(1), 73–101. https://doi.org/10.1080/13594320500451247

Oreg, S. (2017). Resistance to change and performance: toward a more even-handed view of dispositional resistance. *The Journal of Applied Behavioral Science*, *54*(1), 88–107. https://doi.org/10.1177/0021886317741867

Pai, F. Y., & Huang, K. I. (2011). Applying the technology acceptance model to the introduction of healthcare information systems. *Technological Forecasting and Social Change*, *78*(4), 650-660.

Pallant, J. (2013). *SPSS survival manual*. McGraw-Hill Education (UK).

Philips (2019). Future health index 2019 South Africa country report. Retrieved from: https://www.philips.co.za/c-dam/corporate/newscenter/za/2019/2019-fhi-report-south-Africa.pdf

Rathert, C., Mittler, J. N., Banerjee, S., & McDaniel, J. (2017). Patient-centered communication in the era of electronic health records: what does the evidence say? *Patient Education and Counseling*, *100*(1), 50–64. https://doi.org/10.1016/j.pec.2016.07.031

Ramjee, S., Abraham, M., Kaplan, J., Taylor, R., & Vieyra, T. (2013). National health insurance and South Africa's private sector. *South African Health Review*, *2013*(1), 93-103.

Rizer, M. K., Kaufman, B., Sieck, C. J., Hefner, J. L., & McAlearney, A. S. (2015). Top 10 lessons learned from electronic medical record implementation in a large academic medical center. *Perspectives in Health Information Management*, *12*(Summer), 1g–1g. PubMed. https://pubmed.ncbi.nlm.nih.gov/26396558

Rogers, E. M. (1995). Diffusion of Innovations: modifications of a Model for Telecommunications. In *Die Diffusion von Innovationen in der Telekommunikation* (pp. 25–38). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-79868-9_2

Sadoughi, F., Khodaveisi, T., & Ahmadi, H. (2019). The used theories for the adoption of electronic health record: a systematic literature review. *Health and Technology*, *9*(4), 383–400. https://doi.org/10.1007/s12553-018-0277-8

Sadoughi, F., Nasiri, S., & Ahmadi, H. (2018). The impact of health information exchange on healthcare quality and cost-effectiveness: a systematic literature review.

Computer Methods and Programs in Biomedicine, *161*, 209–232. https://doi.org/10.1016/j.cmpb.2018.04.023

Safi, S., Thiessen, T., & Schmailzl, K. J. (2018). Acceptance and resistance of new digital technologies in medicine: qualitative study. *JMIR Research Protocols*, *7*(12). https://doi.org/10.2196/11072

Saunders, M., & Lewis, P. (2018). *Doing research in business and management: an essential guide to planning your project* (2nd edition). *Pearson Education Limited, England.*

Sebetci, Ö. (2018). Enhancing end-user satisfaction through technology compatibility: an assessment on health information system. *Health Policy and Technology*, *7*(3), 265–274. https://doi.org/10.1016/j.hlpt.2018.06.001

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Hu, Y. (2019). Investigating the adoption of big data analytics in healthcare: The moderating role of resistance to change. *Journal of Big Data*, *6*(1), 6. https://doi.org/10.1186/s40537-019-0170-y

Shanafelt, T. D., Dyrbye, L. N., Sinsky, C., Hasan, O., Satele, D., Sloan, J., & West, C. P. (2016). Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction. *Mayo Clinic Proceedings*, *91*(7), 836–848. https://doi.org/10.1016/j.mayocp.2016.05.007

Simon, S. R., Kaushal, R., Cleary, P. D., Jenter, C. A., Volk, L. A., Orav, E. J., Burdick, E., Poon, E. G., & Bates, D. W. (2007). Physicians and electronic health records: a statewide survey. *Archives of Internal Medicine*, *167*(5), 507–512. https://doi.org/10.1001/archinte.167.5.507

Statistics South Africa (2018). Mid-year population estimates. Retrieved from: http://www.statssa.gov.za/?p=11341

Tall, J. M., Hurd, M., & Gifford, T. (2015). Minimal impact of an electronic medical records system. *The American Journal of Emergency Medicine*, *33*(5), 663–666. https://doi.org/10.1016/j.ajem.2015.02.022

Tanwar, S., Parekh, K., & Evans, R. (2020). Blockchain-based electronic healthcare record system for healthcare 4.0 applications. *Journal of Information Security and Applications*, *50*, 102407. https://doi.org/10.1016/j.jisa.2019.102407

Tarabichi, Y., Goyden, J., Liu, R., Lewis, S., Sudano, J., & Kaelber, D. C. (2020). A step closer to nationwide electronic health record–based chronic disease surveillance: characterizing asthma prevalence and emergency department utilization from 100 million patient records through a novel multisite collaboration. *Journal of the American Medical Informatics Association*, *27*(1), 127–135. https://doi.org/10.1093/jamia/ocz172

van der Burgt, S. M. E., Kusurkar, R. A., Wilschut, J. A., Tjin A Tsoi, S. L. N. M., Croiset, G., & Peerdeman, S. M. (2019). Medical specialists' basic psychological needs, and motivation for work and lifelong learning: a two-step factor score path analysis. *BMC Medical Education*, *19*(1), 339. https://doi.org/10.1186/s12909-019-1754-0

Venkatesh, V., & Davis, F. D. (2000). A theoretical acceptance extension model: four longitudinal field studies. *Management Science*, *46*(2), 186–204.

Venkatesh, V., Morris, Davis, G., & Davis, F. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: a synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376.

Wani, D., & Malhotra, M. (2018). Does the meaningful use of electronic health records improve patient outcomes? *Journal of Operations Management*, *60*(1), 1–18. https://doi.org/10.1016/j.jom.2018.06.003

Wegner, T. (2010). *Applied business statistics: methods and excel-based applications*. Juta and Company ltd.

Winchester, M. S., & King, B. (2018). Decentralization, healthcare access, and inequality in Mpumalanga, South Africa. *Health & Place*, *51*, 200–207. https://doi.org/10.1016/j.healthplace.2018.02.009

World Health Organization. (2015). *Tracking universal health coverage: first global monitoring report*. World Health Organization.

World Health Organization. (2019). *World health statistics 2019: monitoring health for the SDGs, sustainable development goals*.

Wu, J.-H., Kao, H.-Y., & Sambamurthy, V. (2016). The integration effort and E-health compatibility effect and the mediating role of E-health synergy on hospital performance. *International Journal of Information Management*, *36*(6), 1288–1300.

Yen, P.-Y., McAlearney, A. S., Sieck, C. J., Hefner, J. L., & Huerta, T. R. (2017). Health information technology (hit) adaptation: refocusing on the journey to successful hit implementation. *JMIR Medical Informatics*, *5*(3), e28. https://doi.org/10.2196/medinform.7476

APPENDIX 1: Consistency matrix

Table 21

Consistency Matrix

	Construct / Variable	Scaled Variable	Questionnaire Items	Source
UTAUT	Performance Expectancy (PE)	PE	PE1: I find EHR system useful in my job PE2: Using the EHR system enables me to accomplish tasks more efficiently PE3: Using EHR increases my productivity PE4: By use of the EHR system, I will increase my chances of getting a salary raise or promotion	
	Effort Expectancy (EE)	EE	EE1: My interaction with EHR system is clear and understandable EE2: It would be easy for me to become skilful at using the EHR system EE3: I find the EHR system easy to operate	
	Social Influence (SI)	SI	SI1: People who are important to me recommend the use of the EHR system SI2: People who influence my behaviour think I should use the EHR system SI3: Senior hospital management has motivated me in the use of the EHR system	(Venkatesh et al., 2003)
	Facilitating Conditions (FC)	FC	FC1: I have the resources necessary to use the EHR system FC2: I have the necessary knowledge and training to use the EHR system FC3: The EHR system is compatible with other systems I use FC4: A special person (or group) is available for assistance with difficulties experienced with the EHR system	(Bawack & Kamdjoug, 2018)
	Behavioural Intention (BI)	BI	BI1: I intend to use EHR in my job BI2: I expect to use EHR in my job BI3: I plan to use EHR within a year BI4: I predict I would use EHR within a year	Venkatesh et al., 2012
Psychological / Individual Factor	Resistance to Change	RC	RC1: I don't want the EHR system to change the way I manage the diseases of my patients. RC2: I don't want the EHR system to change the way I keep the health records of patients. RC3: I don't want the EHR system to change the way I interact with other physicians regarding my patients' diseases.	(Bhattacherjee & Hikmet, 2008)
Change Attitude Scale	Affective	A	A1: I was fearful of the change A2: I had a bad feeling about the change A3: I was quite excited about the change A4: The change made me upset A5: I was stressed by the change	(Oreg, 2006)
	Behavioural	B	B1: I looked for ways to prevent the change from taking place B2: I protested against the change B3: I complained about the change to my colleagues B4: I presented my objections regarding the change to management B5: I spoke rather highly of the change to others	
	Cognitive	C	C1: I believed that the change would harm the way things are done in the organisation C2: I thought that it's a negative thing that we were going through this change C3: I believed that the change would make my job more difficult C4: I believed that the change would benefit the organisation C5: I believed that I could personally benefit from the change	

APPENDIX 2: Letter of consent

Gordon Institute of Business Science
University of Pretoria

Ethics Reference No.: 689/2019

MBA Research: Predicting Clinicians' Intentions Towards the Electronic Health Record (EHR): An Extended UTAUT Model

Dear Respondent,

I am a medical doctor and currently a student at the University of Pretoria's Gordon Institute of Business Science. As part of my fulfillment of my MBA, I am conducting research investigating the factors influencing physicians' intentions toward a form of Health Information Technology (HIT). By definition, HIT can take the form of services such as:

- Mobile health (mHealth),
- Telemedicine,
- The Electronic Health Record (EHR) system, and
- Decision Support Systems (DSS).

This research study will only focus on the EHR system. An EHR system is defined as a store of health sensitive information in a digital format that can be safely held and exchanged. Only physicians are requested to partake in this research as physicians have been identified as the key deciding stakeholders in utilising electronic health platforms and have the ability to influence technology use within the healthcare community. Therefore, you are kindly requested to complete a questionnaire for this study based on your experience with the EHR system which should take no longer than 15 minutes to complete. The survey includes questions on non-identifying demographics, your daily experience using the EHR system, as well as your feelings towards the EHR system. This will help us better understand the relationships influencing your intentions toward information technology in healthcare. Your participation is anonymous and only aggregated data will be reported. By completing this survey, you indicate that you voluntarily participate in this research. No compensation for participation will be granted and you may withdraw at any time without penalty. If you have any concerns, please do contact me or my supervisor. Details are provided below.

Researcher: Dr Robyn Johnson

Email: 28120664@mygibs.co.za

Phone: 082 628 7773

Supervisor: Dr Jonathan Marks

Email: marksj@gibs.co.za

Phone: 082 469 0104

APPENDIX 3: Questionnaire

PART A: Please answer the following questions.
Demographics
What is your gender?
☐ Male ☐ Female
What is your age (years)?
☐ Less than 25 ☐ 25-30 ☐ 31-35 ☐ 36-40 ☐ 41-45 ☐ 46-50 ☐ 51-55 ☐ More than 55
What is your speciality? (i.e. General Practitioner) _____
How many years of experience do you have in the medical field?
☐ Less than 1 year ☐ 1-3 years ☐ 4-6 years ☐ More than 10 years
How many years have you used IT (i.e. a computer system) in healthcare?
☐ Less than 1 year ☐ 1-3 years ☐ 4-6 years ☐ More than 10 years
Are you willing to use the Electronic Health Record (EHR) system?
☐ Yes ☐ No ☐ Maybe
Are you currently using or have any experience using the EHR system?
☐ Yes ☐ No (if answered no, proceed to the end of the questionnaire ---→ Thank you for taking the time to complete this survey!)

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Disagree
PART B: Please answer the questions below based on your experience using the EHR system					
Performance Expectancy (PE)					
1. I find EHR useful in my job	1	2	3	4	5
2. Using EHR would enable me to accomplish tasks more efficiently	1	2	3	4	5
3. Using EHR increases my productivity	1	2	3	4	5
4. By use of the EHR system, I will increase my chances of getting a raise or promotion	1	2	3	4	5
Effort Expectancy (EE)					
1. My interaction with EHR is clear and understandable	1	2	3	4	5
2. It would be easy for me to become skilful at using the EHR system	1	2	3	4	5
3. I find the EHR system easy to operate	1	2	3	4	5
Social Influence (SI)					
1. People who are important to me recommend the use of the EHR system	1	2	3	4	5
2. People who influence my behaviour think I should use the EHR system	1	2	3	4	5
3. Senior hospital management has motivated me in the use of the EHR system	1	2	3	4	5
Facilitating Conditions (FC)					
1. I have the resources necessary to use the EHR system	1	2	3	4	5
2. I have the necessary knowledge and training to use EHR	1	2	3	4	5
3. The EHR system is compatible with other systems I use	1	2	3	4	5
4. A specific person (or group) is available for assistance with difficulties experienced with the EHR system	1	2	3	4	5
Resistance to Change (RC)					
1. I don't want the EHR system to change the way I manage the diseases of my patients	1	2	3	4	5
2. I don't want the EHR system to change the way I keep the health records of my patients	1	2	3	4	5
3. I don't want the EHR system to change the way I interact with other physicians regarding my patients' diseases	1	2	3	4	5

PART C: Please reflect on your experience at a time when the EHR system was being implemented at your work facility and answer the following questions.					
Affective (A)					
1. I was fearful of the change	1	2	3	4	5
2. I had a bad feeling about the change	1	2	3	4	5
3. I was quite excited by the change*	1	2	3	4	5
4. The change made me upset	1	2	3	4	5
5. I was stressed by the change	1	2	3	4	5
Behavioural (B)					
1. I looked for ways to prevent the change from taking place	1	2	3	4	5
2. I protested against the change	1	2	3	4	5
3. I complained about the change to my colleagues	1	2	3	4	5
4. I presented my objections regarding the change to management	1	2	3	4	5

5. I spoke rather highly of the change to others*	1	2	3	4	5
Cognitive (C)					
1. I believed that the change would harm the way things are being done in the organization	1	2	3	4	5
2. I thought that it was a negative thing that we were going through the change	1	2	3	4	5
3. I believed that the change would make my job more difficult	1	2	3	4	5
4. I believed that the change would benefit the organization*	1	2	3	4	5
5. I believed that I could personally benefit from the change*	1	2	3	4	5

PART D: Please answer the following questions regarding your future intentions towards the EHR system.					
Behavioural Intentions (BI)					
1. I intend to use EHR in future	1	2	3	4	5
2. I will always try to use the EHR system	1	2	3	4	5
3. I plan to continue making use of the EHR system more frequently	1	2	3	4	5

*Reverse coded questions.

APPENDIX 4: Correlation matrices

Table 22

Part B Correlation Matrix

Items	PE1	PE2	PE3	PE4	EE1	EE2	EE3	SI1	SI2	SI3	FC1	FC2	FC3	FC4	rRC1	rRC2	rRC3
PE1	**1,000**	0,825	0,748	0,330	0,698	0,567	0,705	0,445	0,278	0,061	0,444	0,503	0,447	0,299	0,123	0,285	0,138
PE2	0,825	**1,000**	0,887	0,426	0,673	0,522	0,736	0,401	0,283	0,035	0,448	0,527	0,420	0,330	0,140	0,150	0,165
PE3	0,748	0,887	**1,000**	0,444	0,659	0,491	0,688	0,393	0,284	0,052	0,392	0,436	0,412	0,248	0,157	0,159	0,195
PE4	0,330	0,426	0,444	**1,000**	0,395	0,337	0,398	0,394	0,306	0,175	0,249	0,212	0,395	0,237	0,145	0,052	0,148
EE1	0,698	0,673	0,659	0,395	**1,000**	0,527	0,753	0,430	0,277	0,097	0,634	0,662	0,574	0,435	0,072	0,164	0,110
EE2	0,567	0,522	0,491	0,337	0,527	**1,000**	0,705	0,327	0,127	0,010	0,441	0,531	0,515	0,249	-0,059	0,061	-0,002
EE3	0,705	0,736	0,688	0,398	0,753	0,705	**1,000**	0,487	0,283	0,044	0,517	0,631	0,666	0,430	0,069	0,175	0,088
SI1	0,445	0,401	0,393	0,394	0,430	0,327	0,487	**1,000**	0,670	0,298	0,201	0,338	0,403	0,369	0,110	0,267	0,096
SI2	0,278	0,283	0,284	0,306	0,277	0,127	0,283	0,670	**1,000**	0,468	0,141	0,198	0,284	0,342	0,056	0,193	0,072
SI3	0,061	0,035	0,052	0,175	0,097	0,010	0,044	0,298	0,468	**1,000**	0,168	0,169	0,022	0,194	-0,049	0,113	0,037
FC1	0,444	0,448	0,392	0,249	0,634	0,441	0,517	0,201	0,141	0,168	**1,000**	0,727	0,493	0,574	-0,108	0,057	-0,066
FC2	0,503	0,527	0,436	0,212	0,662	0,531	0,631	0,338	0,198	0,169	0,727	**1,000**	0,546	0,600	-0,064	0,085	-0,008
FC3	0,447	0,420	0,412	0,395	0,574	0,515	0,666	0,403	0,284	0,022	0,493	0,546	**1,000**	0,416	0,007	0,055	-0,056
FC4	0,299	0,330	0,248	0,237	0,435	0,249	0,430	0,369	0,342	0,194	0,574	0,600	0,416	**1,000**	-0,040	0,186	0,080
rRC1	0,123	0,140	0,157	0,145	0,072	-0,059	0,069	0,110	0,056	-0,049	-0,108	-0,064	0,007	-0,040	**1,000**	0,484	0,592
rRC2	0,285	0,150	0,159	0,052	0,164	0,061	0,175	0,267	0,193	0,113	0,057	0,085	0,055	0,186	0,484	**1,000**	0,598
rRC3	0,138	0,165	0,195	0,148	0,110	-0,002	0,088	0,096	0,072	0,037	-0,066	-0,008	-0,056	0,080	0,592	0,598	**1,000**

Table 23

Part C Correlation Matrix

Items	A1	A2	rA3	A4	A5	B1	B2	B3	B4	rB5	C1	C2	C3	rC4	rC5
A1	**1,000**	0,681	0,145	0,351	0,418	0,320	0,280	0,291	0,164	-0,020	0,365	0,344	0,389	0,096	0,111
A2	0,681	**1,000**	0,281	0,467	0,470	0,461	0,424	0,525	0,345	0,115	0,450	0,432	0,491	0,232	0,244
rA3	0,145	0,281	**1,000**	0,203	0,100	0,314	0,190	0,226	0,187	0,446	0,305	0,300	0,276	0,424	0,468
A4	0,351	0,467	0,203	**1,000**	0,611	0,671	0,677	0,651	0,447	0,155	0,586	0,593	0,551	0,171	0,169
A5	0,418	0,470	0,100	0,611	**1,000**	0,500	0,372	0,512	0,242	0,129	0,418	0,387	0,566	0,232	0,242
B1	0,320	0,461	0,314	0,671	0,500	**1,000**	0,615	0,603	0,418	0,248	0,515	0,515	0,462	0,183	0,154
B2	0,280	0,424	0,190	0,677	0,372	0,615	**1,000**	0,738	0,678	0,122	0,541	0,607	0,402	0,225	0,153
B3	0,291	0,525	0,226	0,651	0,512	0,603	0,738	**1,000**	0,636	0,228	0,631	0,636	0,619	0,306	0,328
B4	0,164	0,345	0,187	0,447	0,242	0,418	0,678	0,636	**1,000**	0,103	0,526	0,559	0,421	0,287	0,348
rB5	-0,020	0,115	0,446	0,155	0,129	0,248	0,122	0,228	0,103	**1,000**	0,223	0,248	0,183	0,454	0,487
C1	0,365	0,450	0,305	0,586	0,418	0,515	0,541	0,631	0,526	0,223	**1,000**	0,692	0,637	0,224	0,264
C2	0,344	0,432	0,300	0,593	0,387	0,515	0,607	0,636	0,559	0,248	0,692	**1,000**	0,622	0,267	0,291
C3	0,389	0,491	0,276	0,551	0,566	0,462	0,402	0,619	0,421	0,183	0,637	0,622	**1,000**	0,289	0,414
rC4	0,096	0,232	0,424	0,171	0,232	0,183	0,225	0,306	0,287	0,454	0,224	0,267	0,289	**1,000**	0,747
rC5	0,111	0,244	0,468	0,169	0,242	0,154	0,153	0,328	0,348	0,487	0,264	0,291	0,414	0,747	**1,000**

Table 24

Part D Correlation Matrix

Items	BI1	BI2	BI3
BI1	**1,000**	0,853	0,841
BI2	0,853	**1,000**	0,915
BI3	0,841	0,915	**1,000**

APPENDIX 5: Anti-image matrices

Table 25

Part B Anti-Image Matrix

Item	PE1	PE2	PE3	PE4	EE1	EE2	EE3	SI1	SI2	SI3	FC1	FC2	FC3	FC4	rRC1	rRC2	rRC3
PE1	**.875[a]**	-0,500	0,017	0,141	-0,275	-0,217	0,063	-0,115	0,044	-0,033	-0,003	0,085	-0,056	0,072	0,032	-0,309	0,134
PE2	-0,500	**.809[a]**	-0,648	-0,140	0,144	0,123	-0,257	0,079	-0,091	0,119	-0,020	-0,188	0,201	-0,070	-0,065	0,181	-0,051
PE3	0,017	-0,648	**.878[a]**	-0,073	-0,169	-0,026	-0,032	-0,014	-0,030	-0,033	-0,022	0,119	-0,043	0,127	0,015	0,008	-0,087
PE4	0,141	-0,140	-0,073	**.840[a]**	-0,109	-0,165	0,091	-0,174	0,023	-0,155	-0,056	0,229	-0,219	-0,080	-0,096	0,139	-0,105
EE1	-0,275	0,144	-0,169	-0,109	**.908[a]**	0,167	-0,305	-0,050	-0,027	0,055	-0,290	-0,200	-0,034	0,074	-0,007	0,081	-0,098
EE2	-0,217	0,123	-0,026	-0,165	0,167	**.868[a]**	-0,423	-0,033	0,065	0,049	-0,087	-0,190	-0,030	0,179	0,132	0,042	-0,056
EE3	0,063	-0,257	-0,032	0,091	-0,305	-0,423	**.893[a]**	-0,130	0,070	0,006	0,114	-0,031	-0,344	-0,109	-0,009	-0,082	0,034
SI1	-0,115	0,079	-0,014	-0,174	-0,050	-0,033	-0,130	**.845[a]**	-0,515	-0,017	0,195	-0,095	-0,012	-0,087	-0,035	-0,131	0,101
SI2	0,044	-0,091	-0,030	0,023	-0,027	0,065	0,070	-0,515	**.743[a]**	-0,392	0,067	0,128	-0,143	-0,169	0,015	-0,022	0,027
SI3	-0,033	0,119	-0,033	-0,155	0,055	0,049	0,006	-0,017	-0,392	**.615[a]**	-0,134	-0,162	0,182	0,068	0,088	-0,047	-0,036
FC1	-0,003	-0,020	-0,022	-0,056	-0,290	-0,087	0,114	0,195	0,067	-0,134	**.868[a]**	-0,340	-0,101	-0,296	0,039	-0,076	0,140
FC2	0,085	-0,188	0,119	0,229	-0,200	-0,190	-0,031	-0,095	0,128	-0,162	-0,340	**.877[a]**	-0,136	-0,285	-0,004	0,046	-0,011
FC3	-0,056	0,201	-0,043	-0,219	-0,034	-0,030	-0,344	-0,012	-0,143	0,182	-0,101	-0,136	**.894[a]**	-0,045	-0,080	0,039	0,119
FC4	0,072	-0,070	0,127	-0,080	0,074	0,179	-0,109	-0,087	-0,169	0,068	-0,296	-0,285	-0,045	**.853[a]**	0,135	-0,108	-0,113
rRC1	0,032	-0,065	0,015	-0,096	-0,007	0,132	-0,009	-0,035	0,015	0,088	0,039	-0,004	-0,080	0,135	**.725[a]**	-0,232	-0,387
rRC2	-0,309	0,181	0,008	0,139	0,081	0,042	-0,082	-0,131	-0,022	-0,047	-0,076	0,046	0,039	-0,108	-0,232	**.671[a]**	-0,459
rRC3	0,134	-0,051	-0,087	-0,105	-0,098	-0,056	0,034	0,101	0,027	-0,036	0,140	-0,011	0,119	-0,113	-0,387	-0,459	**.647[a]**

a. Measures of Sampling Adequacy (MSA)

a. Measures of Sampling Adequacy (MSA)

Table 26

Part C Anti-Image Matrix

Item	A1	A2	rA3	A4	A5	B1	B2	B3	B4	rB5	C1	C2	C3	rC4	rC5
A1	**.758[a]**	-0,595	0,027	0,038	-0,148	-0,002	-0,093	0,191	0,123	0,123	-0,109	-0,099	-0,041	0,033	-0,034
A2	-0,595	**.850[a]**	-0,145	-0,019	-0,052	-0,068	0,038	-0,226	-0,062	0,015	0,029	0,045	-0,049	-0,042	0,022
rA3	0,027	-0,145	**.847[a]**	0,000	0,184	-0,204	-0,023	0,118	0,083	-0,200	-0,109	-0,047	-0,027	-0,084	-0,206
A4	0,038	-0,019	0,000	**.912[a]**	-0,337	-0,246	-0,324	-0,014	0,098	0,014	-0,117	-0,109	-0,071	0,071	-0,005
A5	-0,148	-0,052	0,184	-0,337	**.879[a]**	-0,154	0,099	-0,126	0,109	0,006	0,032	0,092	-0,235	-0,102	-0,043
B1	-0,002	-0,068	-0,204	-0,246	-0,154	**.932[a]**	-0,166	-0,086	-0,022	-0,157	-0,020	0,008	-0,020	0,022	0,138
B2	-0,093	0,038	-0,023	-0,324	0,099	-0,166	**.847[a]**	-0,378	-0,396	0,042	0,046	-0,140	0,196	-0,154	0,190
B3	0,191	-0,226	0,118	-0,014	-0,126	-0,086	-0,378	**.914[a]**	-0,138	-0,081	-0,121	-0,039	-0,219	0,007	-0,069
B4	0,123	-0,062	0,083	0,098	0,109	-0,022	-0,396	-0,138	**.863[a]**	0,187	-0,159	-0,136	0,019	0,054	-0,288
rB5	0,123	0,015	-0,200	0,014	0,006	-0,157	0,042	-0,081	0,187	**.807[a]**	-0,081	-0,122	0,135	-0,106	-0,245
C1	-0,109	0,029	-0,109	-0,117	0,032	-0,020	0,046	-0,121	-0,159	-0,081	**.933[a]**	-0,280	-0,237	0,018	0,085
C2	-0,099	0,045	-0,047	-0,109	0,092	0,008	-0,140	-0,039	-0,136	-0,122	-0,280	**.934[a]**	-0,254	-0,030	0,053
C3	-0,041	-0,049	-0,027	-0,071	-0,235	-0,020	0,196	-0,219	0,019	0,135	-0,237	-0,254	**.896[a]**	0,091	-0,244
rC4	0,033	-0,042	-0,084	0,071	-0,102	0,022	-0,154	0,007	0,054	-0,106	0,018	-0,030	0,091	**.779[a]**	-0,607
rC5	-0,034	0,022	-0,206	-0,005	-0,043	0,138	0,190	-0,069	-0,288	-0,245	0,085	0,053	-0,244	-0,607	**.721[a]**

a. Measures of Sampling Adequacy (MSA)

Table 27

Part D Anti-Image Matrix

Item	BI1	BI2	BI3
BI1	**.863[a]**	-0,382	-0,288
BI2	-0,382	**.711[a]**	-0,700
BI3	-0,288	-0,700	**.730[a]**

a. Measures of Sampling Adequacy (MSA)

APPENDIX 6: Scree plots for UTAUT model

PART B FACTOR ANALYSIS

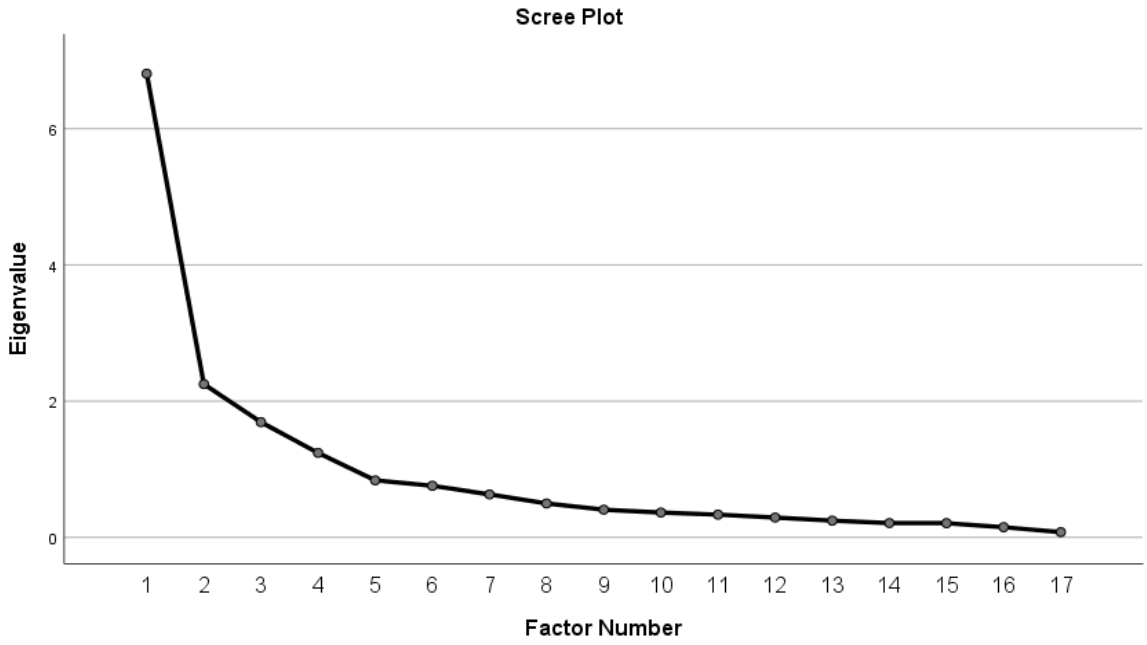

Figure 11: Scree plot for Part B Factor analysis

PART D FACTOR ANALYSIS

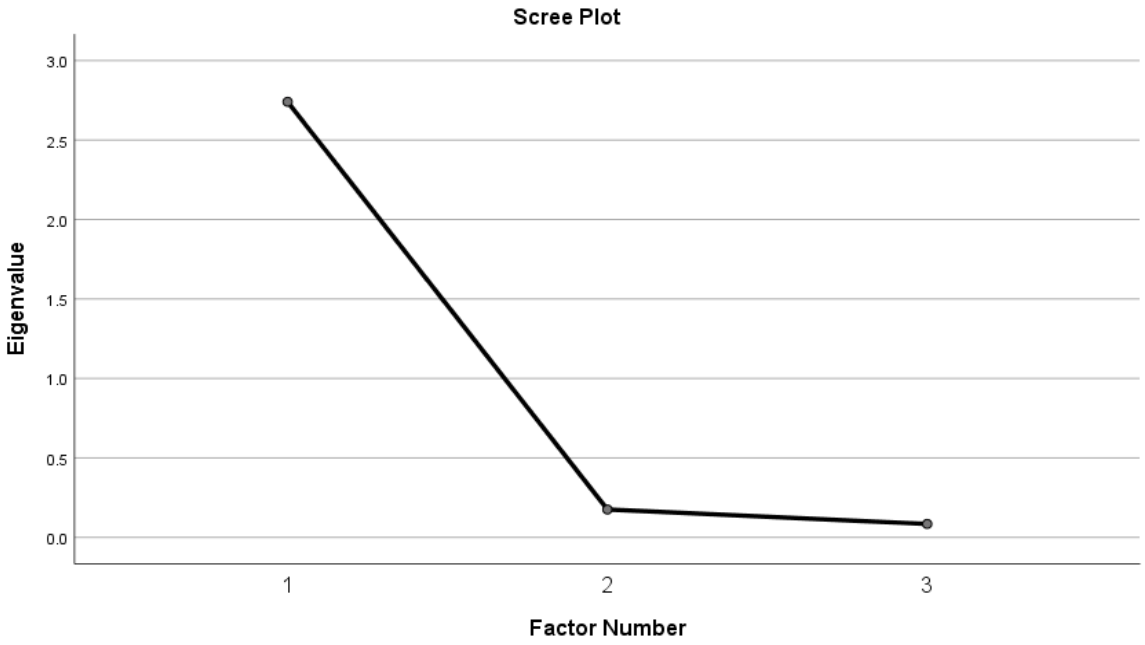

Figure 12: Scree plot relevant for Part D Factor analysis

APPENDIX 7: Scree plot for change attitude scale

PART C FACTOR ANALYSIS

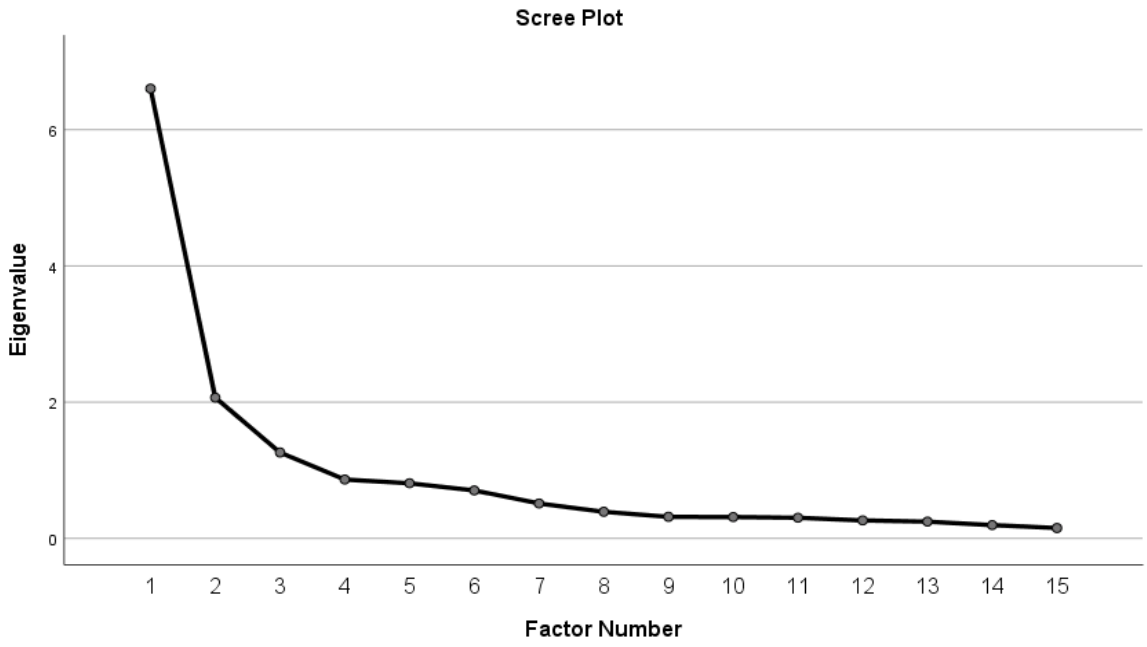

Figure 13: Scree plot relevant for Part C Factor analysis