Modelling the critical success factors for evidence-based healthcare practice at a South African public hospital

by

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DECLARATION

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I hereby declare that **Modelling the Critical Success Factors for Evidence-Based Healthcare Practice at a South African Public Hospital** is entirely my own, original work and all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

I further declare that I have never before submitted this work, in whole or in part, to UNISA for a qualification examination or to any other higher education institution.

18/07/2023

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DEDICATION

To the Glory of the Almighty, I am proud to say: “I have done it for the second time”. I also want to dedicate my work to the medical healthcare professionals that battled to stop the spread of Covid-19 in various parts of the world. We are grateful for everything they have done, including daily risking their lives to keep us safe from the Covid-19 pandemic. We appreciate them for being on the front line during that very daunting time of our lives.

ABSTRACT

This study aimed to investigate the critical success factors for the adoption of evidence-based healthcare practice at a Dr George Mukhari Academic hospital (DGMAH). The updated DeLone & McLean's updated information systems success model (D&M IS Success Model), the technological, organisational, and environmental (TOE) framework and the technological acceptance model (TAM) were used as the underpinning theories to develop the hybrid model. Structural equation modelling (SEM) was utilised to validate and test the proposed model. Data for the study were gathered using a self-administered questionnaire for medical healthcare professionals at DGMAH. The findings of the study show that the electronic health records (EHR) construct had a significant positive influence on information quality (IQ), knowledge quality (KQ) and diagnosis and treatment of diseases (DTD) in the final model, with values of (β =0.558, ($p<0.05$), (β=0.558, ($p <0.05$) and (β =0.558, ($p <0.05$), respectively.

Similarly, the study's findings also revealed a significant and positive correlation between two constructs: the adoption of evidence-based healthcare practice (EBHP) ($r=0.299$; $p<0.05$) and better coordination of patient care ($r=0.294$; $p<0.05$). Better patient care coordination is positively and significantly correlated with EHR ($r= 0.121$, $p<0.05$), DTD ($r=0.173$, p0.05), IQ ($r= 0.221$, $p<0.05$) and KQ ($r=0.181$, $p<0.05$). The path analysis' findings demonstrated that the goodness of fit indices including the goodness of fit index (GFI) of 0.905, the comparative fit index (CFI) of 0.905 and the root mean square error of approximation (RMSEA) of 0.035 were all within the acceptable range of values.

This study contributed to the development of a new framework that identified the critical success factors for EBHP at a public hospital in South Africa. The study's findings also make a considerable contribution to the body of knowledge in the fields of health informatics, particularly eHealth. Policymakers at the Department of Health as well as healthcare professionals who are sectional heads of different hospital departments may adopt the developed framework as a guideline on how to adopt and implement EBHP in public hospitals, as well as the critical success factors that need to be considered. Future research employing qualitative research methodologies

should investigate additional factors that may have an impact on the adoption of EBHP.

Keywords: Electronic health records, evidence-based healthcare practice, diagnosis and treatment of diseases, information quality, knowledge quality

LIST OF ABBREVIATIONS

AGFI	Adjusted Goodness of Fit Index AGFI
AMOS	Analysis of Moment Structures
CMA	Canadian Medical Association
CMIN	Chi-square
CMIN/DF	Chi-square per Degrees of Freedom
CFI	Comparative Fit Index
DTD	Diagnosis of Diseases and Treatment
EC	Ethical Clearance
CFA	Confirmatory Factor Analysis
CSFs	Critical Success Factors
DF	Degrees of Freedom
DOI	Diffusion of Innovation DOI
DHIMS	District Health Management Information System
DGMAH	Dr George Mukhari Academic Hospital
EDI	Electronic Data Interchange
EHIT	Electronic Health Information Technology
HER	Electronic Health Records
EC	Environment Context
EBHP	Evidence-Based Healthcare Practice
EBM	Evidence-Based Medicine
EBP	Evidence-Based Practice
EFA	Exploratory Factor Analysis
GFI	Goodness of Fit Index
HAMS	Health Administration Management System
HIT	Health Information Technology
HCP	Healthcare Professionals
ICT	Information and Communication Technology
IQ	Information Quality
IS	Information System
IT	Information Technology
KMO	Kaiser-Meyer-Olkin
KQ	Knowledge Quality
ML	Maximum Likelihood

MER	Medical Error Reduction
MHCP	Medical Healthcare Professionals
MOH	Ministry of Health
NdoH	National Department of Health
NHHRC	National Health and Hospital Reform Commission
NHIS	National Health Insurance Scheme
HNSF	National Health Normative Standards Framework for eHealth in South Africa
NHS	National Health System
NFI	Normed Fit Index
OC	Organisation Context
OECD	Organisation for Economic Cooperation and Development
PBC	Perceived Behavioural Control
PHR	Personal Health Record
PCP	Primary Care Practice
RMSEA	Root Mean Square Error of Approximation
RMR	Root Mean Square
SET	Social Exchange Theory
SA	South Africa
SD	Standard Deviation
SPSS	Statistical Package for Social Scientists
SEM	Structural Equation Modelling
TC	Technical Context
TAM	Technology Acceptance Model
TOE	Technology-Organisation-Environment framework
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
UK	United Kingdom
UNISA	University of South Africa
VIF	Variance Inflation Factor
WHO	World Health Organisation

PUBLICATIONS FROM THE STUDY

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Motsi. L. & Chimbo, B. (2024). Evidence-based healthcare practice adoption: The impact of electronic health records. *Africa's Public Service Delivery and Performance.* 12(1), doi: https://doi.org/10.4102/apsdpr.v12i1.728

Motsi. L (2024). Investigating the influencing factors of evidence-based healthcare practice adoption. *Curationis.* 47(1), doi: https://doi.org/10.4102/curationis.v47i1.2586

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Motsi. L. (2024). EHR model to reduce patients' treatment costs and improved quality of healthcare, 29 (1), Health SA Gesondheid. doi: https://doi.org/10.4102/hsag.v29i0.2414.

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CHAPTER 1: INTRODUCTION

This chapter provides the introduction, background, statement of the problem, research questions and the significance of the study.

1.1 BACKGROUND TO THE RESEARCH PROBLEM

Economic prosperity requires a high-quality populace, and the populace's general health determines this (Muhanga & Malungo, 2018; Muhanga, 2020). According to the Sustainable Development Goals, a strong local economy and a commitment to growth go hand in hand (UNDP, 2015; URT, 2016). Effective and efficient healthcare delivery are important elements that, among other things, promote optimum health (Muhanga & Mapoma, 2019). Ayabakan, Bardhan, Zheng, and Kirksey (2017) assert that health information systems (HIS) make it easier to collect, store, distribute, and retrieve patient health data. Furthermore, these systems have significant advantages in terms of better information integration, reduced hospital costs, expanded databases with enormous amounts of data, and improved hospital management (Ahmadian, Dorosti, Khajouei & Gohari, 2017).

Paper-based systems are labour-intensive, time-consuming, and frequently produce outdated and useless data as a result of flawed reporting procedures (Raut, Yarbrough, Singh, Gauchan, Citrin & Verma, 2018). The electronic medical record represents a transition from antiquated paper record-keeping to electronic records management in a computerized format, supported by internet network systems, and offering versatility in the ability to transfer information and effect change. As a result, it has come to be recognized as a contemporary facilitator of productivity, efficiency, and effectiveness in medical care (Adeleke, Asiru, Oweghoro, Jimoh & Ndana, 2014; Sockolow, Bowles, Adelsberger, Chittams & Liao, 2014). Recent studies indicate that eHealth is the information and communication technology (ICT) element that enhances health care systems in developing countries (Baryashaba, Musimenta, Mugisha & Binamungu, 2019; Hossain, Quaresma & Rahman, 2019).

The goal of this study was to investigate the critical success factors necessary for the adoption of evidence-based healthcare practice (EBHP) at Dr. George Mukhari Academic Hospital (DGMAH). To accomplish this goal, research questions were developed based on the conceptual framework in Figure 3.2. In number of studies researchers as well as academics have developed a range of theories and models that have been used in various contexts to better understand the technology adoption process (Gurjar, 2018; Koul & Eydgahi, 2017). For scientific studies, a theoretical framework or model is necessary to direct the data collecting and analysis procedure (Fox, Gardner & Osborne 2014). To investigate the critical success factors for the adoption of EBHP this study employed the updated DeLone & McLean's information systems success model (D&M IS Success Model)] (DeLone & McLean, 2003). Technology Acceptance Model (TAM) (Davis, 1989), Technology, Organisation, and Environment (TOE) Framework, were integrated into D&M IS Success Model to develop a conceptual framework depicted in Figure 3.2. Structural equation modelling (SEM) was used to test and validate the conceptual framework using quantitative data collected at DGMAH.

1.2 PROBLEM STATEMENT

South Africa has been striving to adopt EHR systems in both public and private healthcare institutions for a long time but concerns and challenges with managing change throughout the implementation have not been appropriately addressed. In prior research (Luthuli 2017, Marutha, 2016, Thomas, 2016, Katuu, 2015), it was stressed how important it was to implement EHR systems to enhance the delivery of healthcare in South Africa, however the topic of change management has not yet been fully explored. To keep track of a patient’s medical history, a new file is opened at each healthcare facility where patients receive care and treatment. Furthermore, when a patient relocates to a new place, their medical records are kept at the hospital where they received treatment (Wright, O'Mahony, & Cilliers, 2017). Medical healthcare professionals often find it difficult to confirm patients' medical histories since patients or healthcare facilities frequently misplace previous prescriptions and test results.

In accordance with published research, there is a link between a patient’s withholding of health information and error in diagnosis that increases risk and injury to the patient (Zwaan, Monteiro, Sherbino, Ilgen, Howey & Norman, 2017). According to Rycroft-Malone, Burton, Wilkinson, Harvey, McCormack, Baker and Williams (2016), the use of evidence-based practise (EBP) leads to the best patient-centred care, encourages the delivery of more extensive, safe, and high-quality healthcare that enhances health outcomes, decreases disparity, and lowers costs. In order to evaluate the progress made with prior treatments and determine how to proceed, medical healthcare professional require information on prior diagnoses, therapies, and prescriptions. If medical records are not effectively handled, obtaining them can be a challenge, which would make it difficult for hospitals to provide healthcare services for chronic patients particularly or cause these services to be provided erroneously.

At some point in their life, many people will use medications to treat or prevent illness. However, drugs occasionally cause severe harm, incapacitating conditions, and even death if misused (WHO, 2017; Ojerinde & Adejumo, 2017). Medication mistakes are the main causes of preventable patient harm in the worldwide health care system. In African healthcare settings, medication errors frequently result in health problems (WHO, 2017; Mekonnen, Alhawassi & McLachlan, 2018). Mamede, Van Gog, and Sampaio (2014) estimate that 6 to 17% of undesirable events in the hospital setting are the result of diagnostic errors. Medication administration errors (MAEs) are the most prevalent drug errors that can have detrimental effects on patients, healthcare workers, and healthcare facilities (Mekonnen et al., 2018). Patients and the healthcare system are financially burdened by pharmaceutical errors (Jankovic, Pejcic, Milosavljevic, Opancina, Pesic & Nedljkovic, 2018). According to the examined scientific literature, the research gap in this study was the absence of a framework in public health institutions for adopting EBHP. To fill the vacuum in the literature and identify the barriers to EBHP implementation in public hospitals, an in-depth investigation was necessary. The study's primary goal was therefore to develop a framework for the adoption of EBHP at a South African public hospital in Gauteng province. Emparanza, Cabello and Burls (2015) added that a framework would enhance clinical patient outcomes, raise healthcare quality, and lower costs by providing guidelines for the adoption of EBHP in public institutions.

1.3 RESEARCH AIMS AND OBJECTIVES

In this section, the aim and research objectives of the study are discussed.

Aim and Objectives

This study's aim was to investigate the critical success factors that are responsible for the successful implementation of evidence-based healthcare practice (EBHP) at a South African public hospital using DGMDH as a case study. To achieve the aim of the study, the following research objectives were established:

RO1: To identify the critical success factors that determine the implementation of evidence-based healthcare practice at a South African public hospital.

RO2: To determine the influence of electronic health records on medical error reduction, as well as on the diagnosis and treatment of diseases.

RO3: To evaluate the impact of information quality, service quality, knowledge quality as well as better coordination of patient care towards the adoption and implementation of evidence-based healthcare practice.

RO4: To explore the impact of technology-organisation-environment framework (TOE) framework factors towards the adoption and implementation of electronic health records (EHR).

RO5: To determine the influence of ease of use and perceived ease of use towards the adoption and implementation of electronic health records.

RO6: To determine the relevant critical success factors for developing a conceptual framework for the adoption of evidence-based healthcare practice at a South African public hospital.

1.4 RESEARCH QUESTIONS

The following section addresses the main research question and sub-questions.

1.4.1 Main Research Question

How can the critical success factors that should be incorporated into the development of EBHP framework that provides the accurate diagnosis and treatment of patients at a South African public hospital be established?

1.4.2 Sub Research Questions

RQ1: What are the critical success factors for the adoption and implementation of evidence-based healthcare practice at a South African public hospital?

RQ2: What is the influence of electronic health records on medical error reduction, as well as on the diagnosis and treatment of diseases?

RQ3: What is the impact of information quality, service quality, knowledge quality as well as the better coordination of patient care towards the adoption and implementation of EBHP?

RQ4: What is the impact of technology-organisation-environment framework (TOE) framework factors towards the adoption and implementation of electronic health records (EHR)?

RQ5: What is the influence of ease of use and perceived ease of use towards the adoption and implementation of electronic health records?

RQ6: What are the relevant critical success factors for developing a conceptual framework for the adoption of evidence-based healthcare practice at a South African public hospital?

1.5 SIGNIFICANCE OF THE STUDY

The significance of this study is threefold. Further, the findings of the study contribute to the body of knowledge by giving insight into the variables that influence the adoption of of evidence-based healthcare (EBHP) in South African public hospitals using DGMDH as a case study. In addition, no research has been done using the updated D&M IS Success Models, TAM, and TOE to develop an integrated framework to investigate the critical success factors for EBHP adoption. In this study D&M IS Success Model incorporates modified and new constructs such as better coordination of patient care coordination (BCP), medical error reduction (MER), knowledge quality (KQ) and diagnosis and treatment of deceases (DTD). With the addition of these modified and the new introduced constructs in the D&M IS Success Model, provides a new framework for future research.

In addition, this study also makes a significant contribution to the body of knowledge in the field of e-health transformation by developing a theoretical framework for investigating the critical success factors for EBHP that produces high-quality patient care, to avoid unnecessary hospitalization, and lowers patient treatment costs, especially in resource-constrained developing countries. These findings are helpful for district and provincial healthcare administrators, as well as other policymakers and practitioners in the healthcare sector, thanks to the developed framework, which offers a detailed understanding of the EBHP process and highlights all significant factors in the adoption and implementation of EBHP in South African public hospitals. Enhancing the use of evidence-based healthcare practice requires the involvement of all stakeholders. The World Health Organisation (2017) asserts that a health system is made up of the resources that support it, and EBHP is one of those resources. In addition, this study will aid public healthcare organisations in reducing the risk of failure in implementing EBHP in public hospitals. To close the knowledge-action gap and lessen health disparities, the study's findings indicate that EBHP adoption is essential. Knowledge sharing or exchange among healthcare professionals using EHR systems provide more effective health services and products and strengthen the health care system". Also, the findings of this study may be of great value to other academics working on related research topics. These findings could provide a solid foundation for further research in this area.

1.6 DEFINITION OF KEY TERMS

E-health: This is defined as the practice of achieving and preserving health through the use of digital tools and information exchange (PriceWaterhouseCoopers, 2016).

Health Information Technologies (HIT): These tools are utilised in hospitals by medical personnel to support patient care. They must gather, maintain, and analyse data to support the diagnosis, treatment, and prevention of medical conditions (Sirintrapun & Artz, 2016).

Healthcare: This term refers to preserving and regaining health through disease prevention and treatment, especially by trained and certified professionals (Health care, 2017).

The term "Electronic Health Records" (EHR): refers to a digital platform that stores clinical data of patients registered by healthcare providers, such as medical appointments, prescriptions for medications, imageology reports, or other medical information related to the patient's health (Chakravorty, Jha & Barthwal, 2019).

Evidence-based practice (EBP): This research offers fresh insights for EBP, a term for healthcare interventions that incorporate the best available research, clinical knowledge, and patient values and preferences (Warren, McLaughlin, Bardsley, Eich, Esche, Kropkowski & Risch, 2016). Evidence-based practice is also referred to as a type of knowledge that clinicians use to plan and carry out interventions that are known to enhance the quality-of-service delivery and consumer expectations (Rycroft-Malone et al., 2016).

1.7 CHAPTER SUMMARY

It is impossible to overstate how crucial it is for medical professionals to have easy access to patient medical records at any time or location in order to diagnose and treat patients correctly. If public medical healthcare institutions are to use medical records for the benefit of the healthcare sector, they must transition to an EHR. EHRs increase information dependability, save costs, support patient mobility, and improve the quality of care by giving multiple healthcare providers access to patient data. To incorporate evidence-based knowledge into patient care, the right information must be made available at the right time. The inefficient management of clinical records is a problem not only in

South Africa but also in the United States and other countries, where one out of every seven files in medical facilities is lost. Medical records must be handled correctly to make sure that patients receive the best care possible. The next chapter begins with an exhaustive study of the body of research that is currently accessible and then the difficulties that come with implementing e-health in developing countries will be discussed.

1.8 THESIS STRUCTURE

Chapter 1: This chapter provides the background information for the current study as well as the research topic that developed the theoretical framework. It also includes a justification for the study as well as three research questions that aid in the achievement of the study's stated goals. In addition, the chapter discusses the significance of the study. Finally, the chapter lays out the research for the following chapters.

Chapter 2: The use of information systems, the e-health system, and a general overview of the South African healthcare system was discussed in this chapter. Furthermore, the problems relating to a lack of interoperability between different systems in the South African health sector was also discussed. Knowledge management as an integral part of evidence-based practice that supports clinical judgments will also be included in the discussion. The challenges of integrating e-health systems in healthcare in developing countries were also discussed.

The theoretical foundation for this study is presented in Chapter 3 with a background on the literature on technology adoption, followed by a review of the underpinning ideas used in this study. In order to build the research model for this thesis, the updated D&M IS Success Model TAM, and TOE framework were integrated to develop the proposed conceptual framework was also discussed. In addition, the chapter then examines how these models might be applied to analyse organisational adoption, offers a preliminary research model, and states hypotheses for key constructs which were adopted from D&M IS Success Model, TAM, and TOE and the final research model for EBHP was presented in Chapter 6.

In Chapter 4, the chosen study methodology, information about the study philosophy, the research design, and the research techniques used in the data collecting and analysis are explained. The study's instrument for acquiring data is a questionnaire. A description of the development of the measuring scales, information about the study population, and a discussion of sample selection are all included in this chapter. This chapter provides and discusses justifications for the data collection tools and data analysis methods employed for this investigation.

Chapter 5 highlights the findings from the literature reviews in Chapters 2 and 3 about healthcare professionals' success expectations. This analysis comprises the application of suitable statistical methods such as multivariate analysis of variance and factor analysis as well as structural equation modelling on the dependent variables (success indicators). SEM was used to examine alternative measurement constructs, and factor analysis was used to examine any correlations between the eight indicator variables. The composite indicator variables that come from this process were utilised to develop a hypothesised model that structurally depicts the effects of both success and resilience factors on success expectations.

Chapter 6 summarises the findings and explores each of the study's findings in terms of the technological, organisational and environmental contexts in which they were presented in the suggested research model. Theoretical and managerial implications are discussed, followed by an assessment of the study's shortcomings and recommendations for further research.

CHAPTER 2: LITERATURE REVIEW

The background, problem statement, research objectives, significance of the study, and definitions of key terms were all covered in the previous chapter of this thesis. In this chapter the study's related literature is examined, with a focus on information system implementation in the healthcare sector, the e-health system as well as a general overview of the South African healthcare system. In addition, the issues caused by a lack of system interoperability in the South African healthcare sector will also be discussed. Furthermore, knowledge management as a component of evidence-based healthcare practice will also be discussed. Also discussed will be the benefits of eHealth technology in healthcare and the challenges of eHealth integration in both developed and developing countries.

2.1 INTRODUCTION

According to World Health Statistics, the average life expectancy in the African region is 58 years, which is less than the 68-year average in Southeast Asia (WHO, 2015). It should be noted that the global pandemic brought on by the recent epidemic of the new coronavirus COVID-19 may cause 2020 to diverge from this long-standing pattern. In the United States, that statistic rises to more than 87% (Barnett & Berchick, 2016). However, chronic illnesses have a continuous and direct impact on economies, worker productivity and healthcare spending as a whole. Ironically, these diseases already make up two-thirds of the total disease burden in middle-income nations and are projected to increase to three-quarters of the global disease burden by 2030 (Barnett & Berchick, 2016). It is a daunting endeavour to develop ways to improve care for people who become more chronically ill and require regular medical attention but the challenge of finding the means to pay for this new standard of care is just as worrying. Greater concern is caused by the fact that African health indicators lag behind those of the rest of the world, including South Asia and Southeast Asia, who lagged behind Africa when these indicators were measured a few decades ago (KPMG Africa, 2012).

One of the goals of South Africa's eHealth strategy is to develop a solid foundation for future integration and coordination of eHealth projects in the public and private health sectors due to the country's disease burden, such as the TB and HIV (Department of Health, 2012). In addition, the eHealth Strategy promotes efficient ICT use and documentation (Erasmus & Van der Walt, 2015). Despite the adoption of all these anticipated formats, the majority of South African healthcare facilities still submit paperwork (Katurura & Cilliers, 2018). The hospital frequently "opens" a file folder when a patient comes in for treatment. With few known drawbacks, a central repository for records preservation has many benefits. Its simpler to exchange patient medical information between hospitals at any time and from any location (Zhang et al., 2018). Furthermore, it might be possible to deliver medical care faster and keep fewer physical records than would otherwise be necessary.

2.2 HEALTHCARE INFORMATION EXCHANGE (HIE)

The literature on health formation systems is what this section aims to provide. The sharing of data between an accountable care organisation (ACO) and a health information organisation (HIO) is often referred to as “health information exchange” (HIE) according to industry standards and rules (Anderson, Baskerville & Kaul, 2017). Higher patient care standards are attained as a result of an EHR system's use of HIE technology. Select healthcare stakeholders can participate electronically in a patient's continuum of care model with multiple providers (Anderson et al., 2017; Kumar et al., 2017). Federated, centralised, and hybrid are the three most widely used public architectural type models for HIE, a crucial part of the HIT infrastructure (Akhlaq et al., 2017; Kumar et al., 2017; Walker, 2018). The Health Information Technology for Economic and Clinical Health Act (HITECH) has been working towards this automatic data exchange for more than 20 years to build a healthcare facility that provides fewer medical errors, (Pletcher, Livesay & Mach, 2018). One of the HIE objectives that is covered in the current study is the adoption of eHealth in terms of processing clinical care summaries, ePrescribing, surveillance and monitoring of clinical data, and integrating electronic health records (EHR) with laboratory findings (Sittig, Belmont & Singh, 2018). Figure 2.1 depicts a combined EHR for a single patient encounter (Chara, 2011).

Figure 2.1: EHR system components

Source: (Chara, 2011).

Despite advancements in medical technology, healthcare organisations have been reluctant to implement the rules for handling patient data. EHR is considered to be the incorporation of a number of information technologies that would improve clinical decision-making, including test ordering, electronic prescription, decision support systems, digital imaging, and telemedicine. However, integrating such information into standard clinical practice would encourage the usage of a secure and effective healthcare system (Sockolow, Bowles, Adelsberger, Chittams & Liao, 2014). In addition, the EHR system provides information on the patient including monitoring, therapy, diagnosis, billing, insurance information and contact information (Mahmood, Burney, Abbas & Rizwan, 2012).

According to Khalif and Alswailem (2015), HIS is essential for healthcare delivery in hospitals and other health institutions. In addition, this is due to the fact that HIS enables the preservation of multiple patient data types as well as the ability to keep track of all medical treatments that have been given to the patient. Examples of this kind of information include diagnoses, follow-up findings, treatments, and important medical choices. Khalif and Alswailem (2014) assert that the use of HIS can improve patient engagement in their own healthcare, cost-savings, and the performance of healthcare providers. Furthermore, healthcare professionals can give their patients automated choices that will increase their resilience by getting to know their behaviours, beliefs, and preferences (Weaver, Delaney, Weber & Carr, 2016).

2.2.1 Electronic medical records management in public healthcare delivery

It is impossible to overstate the significant advantages that health information systems and related information technologies provide for the delivery of public healthcare. Management information systems are crucial tools in public healthcare facilities for, among other things, monitoring and containing disease outbreaks (Knobler, Mahmoud, Lemon, Mack, Sivitiz & Oberholtzer, 2004 in Umezuruike et al., 2017). Shorter patient wait times and fewer pointless laboratory tests are two more benefits of implementing an electronic health information system for record-keeping in public healthcare facilities. Improvements in operational effectiveness and a decrease in errors will help to raise the bar for patient care and patient safety (Weaver et al., 2016; Naidoo & Wills, 2016).

Studies show that using an electronic health information system makes it simple, easy, and seamless to manage a variety of medical records, including patient information, prescription data, and diagnostic therapies (Yoon, Chang, Kang, Bae & Park, 2014; (Hussein, Crutzen, Gutenberg, Kulnik, Sareban & Niebauer, 2021). An electronic health information system also enables healthcare service providers to collect various viewpoints on diagnostic procedures, care, and treatment, reduce duplication of effort, improve healthcare quality, and increase employee productivity (Ojo & Popoola, 2015). Real-time patient monitoring is a benefit of implementing EHR systems, as was already mentioned (Naidoo & Wills, 2016). The ability for medical professionals to track patients' progress and test results is another critical element of EHR systems.

Patients must be followed up, given after care, and reminded of appointments by healthcare providers. Nearly all of them engage in this to some degree. EHR systems, however, allow medical facilities to use more data sources for patient monitoring (Naidoo & Wills, 2016). In addition, putting an electronic health information system in place in public health facilities has several economical and medical advantages. Reduced medical costs, efficient record-keeping practices, avoiding wasteful filing, preventing damage to or loss of patient information, efficient resource utilisation, and a decline in frequently repeated laboratory tests and other related services are just a few of the financial benefits (Yoon, Park, Schuemie, Park, Kim & Park, 2014).

Integrating an electronic health information system into the public healthcare system facilitates the implementation of basic management tasks such as initiating, planning, controlling, and organising hospital subsystem operations, as well as the reduction of work-related errors and the promotion of accurate and timely communication among all healthcare professionals (Uluc & Ferman, 2016). In addition, it helps hospitals to switch from an outdated care management approach to one that is modern and effective while still providing first-rate patient care. Furthermore, it reveals the link between lower hospital mortality rates, health issues and the extent of eHealth information systems in healthcare facilities (Yoon et al., 2014).

2.3 HEALTHCARE IN SOUTH AFRICA

The healthcare system

The apartheid era (1948–1993), during which the South African healthcare system was extremely fragmented and had a discriminatory impact on four separate racial groups (black, mixed race, Indian, and white), is responsible for many of the system's current issues (Young, 2016). The apartheid system created ten Bantustans, or "ethnic homelands," where Africans were forcibly segregated. In addition, each of these Bantustans maintained a separate department of health and professional associations, which only served to exacerbate the issue (Nevhutalu, 2016). Lack of resources reduced the health system's delivery, which had an especially negative impact on poor populations (Chassin & Loeb, 2016).

Furthermore, the apartheid era, which saw a stark split in the healthcare system and a negative impact on four different racial groups, is where the current problems in the health are rooted (Maphumulo & Bhengu, 2019). Yet it has been noted that the South African healthcare system is two-tiered and socioeconomically segregated (Republic of South Africa Health Department, 2015). Even though everyone in South Africa is entitled to free, publicly funded healthcare, patients can opt to receive treatment at for-profit hospitals and clinics by purchasing private insurance. In South Africa, there are three different categories of hospitals: primary, secondary, and tertiary. According to García-Vera, Merighi, Conz, Silva, Jesus and Muñoz-González (2018), primary health care (PHC) is based on a paradigm that attempts to offer healthcare to as many people as feasible. Many nations must enhance primary care at the local, regional, and national levels to meet the rising population health demands (Bienkowska-Gibbs et al., 2015; Harris & Zwar, 2014). As a result, primary healthcare is the foundation of a country's health system. According to the concept of primary healthcare, it is essential to make healthcare accessible.

Due to the poor quality of care offered there, the majority of South Africans who cannot access private healthcare must put up with long wait times, rude medical staff, and drug shortages in public facilities (Burger & Christian, 2018). Regarding the number of nurses, doctors, and specialists per population treated, there are significant differences between the public and private sectors (Barron & Padarath, 2017). The cost of access is not a major barrier, but for people who live in rural and distant locations, journey times may be prohibitive (Burger & Christian, 2018). The prevention, identification, and treatment of disease are given first priority in Gauteng's primary healthcare system. These programmes also aim to widen access to high-quality, locally based healthcare. According to García-Vera et al. (2018), the PHC level is based on a strategy that delivers healthcare as close to patients as is practical. In addition, it offers a constrained list of laboratory tests without motivating recommendations.

Studies have also revealed that while patients continue to feel frustrated, healthcare professionals benefit most from what is sometimes perceived as quality improvements, such as shorter wait times, better documentation, and altered work processes (Batalden, 2018). This can be seen as a sign that it is challenging for current healthcare organisations to come up with fresh ideas that will significantly alter how the healthcare sector can respond to the challenges it faces (Socialstyrelsen, 2019). Most of South Africa's larger towns have secondary care hospitals, also known as district general hospitals (Coovadia, Jewkes, Barron Sanders & McIntyre, 2009). While some secondary care hospitals use computers to store data, many do not (Marszalek, 2006). Patients who have been referred by primary health care services go to hospitals and specialty outpatient clinics. Effective management, prognosis, and outcomes of illnesses in the hospital setting depend on the development of patient referral systems. Akande (2016) defined referral as "a process by which a health worker transfers the responsibility of care temporarily or permanently to another health professional, social worker, or to the community." Anil Kumar Gupta et al. (2017) proposed a health system strengthening focusing on referrals. The referral system ensures better quality care at all levels while allowing for cost-effective utilisation of health care (Afolaranmi et al., 2018).

Patients are frequently referred to tertiary care facilities when primary and secondary care are insufficient for their condition. Typically, tertiary hospitals have 300 to 1500 beds (Oluseye, Kehinde, Akingbade, Ogunlade, 2019). Demand, however, is extremely high in the public healthcare sector due to a lack of supply and equipment and a strong demand for services. Furthermore, due to the high prevalence of TB, HIV/AIDS and ailments linked to poverty in South Africa, public healthcare facilities are overburdened. As a result, patients with a variety of illnesses are unable to access healthcare services. In addition, patients who seek public healthcare must deal with issues like lengthy wait times, lost medical records, drug shortages, unfriendly staff, subpar infrastructure, insufficient infection controls, compromised employee safety and security, and poor hygiene (Dunjwa, 2016).

Contrarily, private hospitals, clinics, and specialised facilities offer high-quality and improved services, clean facilities, shorter wait times, better infection control, and cutting-edge medical technologies. These facilities include those for surgery, laboratory services, optometry, paediatrics, surgery, dentistry, and cardiology (Mostert-Phipps, 2012), of which the primary issue with is the excessive cost of treatments. Contrarily, the private sector primarily serves people who use medical aid insurances and have middle to high income levels. The majority of South Africans, however, are unable to utilise these services; as a result, they go to public hospitals for medical care and treatment. It is especially crucial to invest in effective healthcare because South Africa and other developing countries have limited resources. Warren et al. (2016) defines evidence-based practice as a method for providing healthcare that integrates the best available research evidence with the judgment and experience of all relevant parties, particurlarly experts, to benefit society. Evidence-based practice, according to Rycroft-Malone *et al.*

(2016), is a flexible strategy that is guided by the accessibility of the best clinical expertise in relation to the situation and the patient's characteristics.

2.4 eHEALTH SYSTEM IN SOUTH AFRICA AND THE CHALLENGES

In South Africa, most hospitals have relied on manually managing records using various classification schemes (Msomi, 2020). To improve service delivery, hospitals have recently shifted to using electronic health records (EHR) systems for their daily operations. The "digital age of medicine is upon us," as Schutzbank and Fernandopulle (2014) stated. South Africa's public sector has acknowledged the value and necessity of developing EHR systems. Marutha and Ngulube (2018) emphasised the significance of implementing EHR systems in public hospitals to achieve specific improvements in records administration. Patient data is represented digitally in electronic health records that are instantly and securely available to authorized users (Katuu, 2016).

EHR system implementation in the public health sector appears to be very challenging (Marutha & Ngulube, 2018). Although some hospitals in South Africa have adopted EHR systems, most of the public health sector still maintains records manually (Katurura & Cilliers, 2018). Hospitals can share current patient data and gain access to medical histories by implementing an EHR system, which facilitates decision-making (Katurura & Cilliers, 2018). Understanding the elements influencing change management and contributing to it is essential for the successful adoption and implementation of an EHR system.

2.4.1 Management of change in the implementation of EHR systems

Change management is one of the essential elements in developing an EHR system (Bellucci & Nguyen, 2014). For the introduction of the South African EHR system to be successful in this regard, change management is still crucial (Marutha, 2016; Katuu, 2016). South Africa is encouraged to adopt EHR systems through an eHealth policy that regulates the use of ICT for medical purposes (Department of Health & CSIR, 2016). It is anticipated that the South African National eHealth Strategy will lead to enhanced patient information systems throughout the nation (e-Health News, 2014). One of the goals of

South Africa's eHealth strategy is to lay a strong foundation for future integration and coordination of eHealth projects in the public and private health sectors (Department of Health & Human Services, 2014).

Erasmus and Van der Walt (2015) elaborated that, the eHealth strategy encourages effective ICT uptake and records management implementation. Due to the quick development of technology, the corporate world now functions differently in the public and private sectors (Shonhe, 2017). Thomas (2016) further stated that relying on technology alone to ensure a hospital's successful EHR system installation is insufficient. The National Archives of Australia (2018) agrees that not all information management issues can be resolved by implementing an electronic records management system in any organisation, including public hospitals.

2.4.2 Impact of interoperability between different systems

To investigate the many problems relating to interoperability in healthcare, Jacob (2015) undertook a study. The researcher is aware that delays within and across medical facilities might result in administrative waste and poor patient results. According to a study by Tilahun and Fritz (2015), medical professionals commonly stop using electronic medical records, a vital part of HIS, because there is no connectivity with widely used reporting systems. The current patient-level morbidity data sources in the country do not uniformly and adequately cover healthcare facilities and the general public (Auld, Kim, Webb, Podewils & Uys, 2013). However, some provinces have implemented a wide range of health information systems, each with a distinct database structure, level of sophistication and operational maturity.

In addition, there are other health information systems in use in various provinces, each with a distinct database structure, level of sophistication and implementation maturity. Although the concept of a fully interoperable EHR system is still in its infancy, clinical informatics systems are increasingly used to manage specialised domain knowledge and perform complex clinical data analysis (Braunstein, 2018). However, putting an interoperability solution into practice requires a significant amount of work, is difficult, and takes a long time. Intricate privacy and security issues, varying technology and data standards, and other challenges are also present (Blumenthal, 2018; Heath, Appan & Gudigantala, 2017).

Delta 9:

UniCare TM is a service that Delta 9 TM offers to healthcare facilities. Ethinks (2013) claims that 108 hospitals and clinics in Southern Africa currently use UniCare TM. In total, there are 88 hospitals, comprising 28 private and 80 governmental facilities. It is possible to implement programs for the efficient management of admissions, pre-admissions, billing, credit control, reporting, dispensing, stock control, retail interface, electronic claim submissions (EDI), and management information. One of the services provided by UniCare TM is patient registration. The following services are also supported by this software: master patient index and records; patient records: HIV/AIDS management appointments, order entry, results reporting, laboratory and laboratory and radiology, operating rooms, accident and emergency, accounts; pharmacy management; dispensing function; stock control; purchase administration; and interface to other software.

Meditech:

Meditech asserts that since 1982, healthcare organisations in Africa and the Middle East have had access to integrated software solutions (Meditech, 2018). The benefits of Meditech's system include the following: Maximum productivity is achieved through functionality tailored to a particular specialty and intuitive, expert and evidence-based navigation; mobile solutions also include physician-driven adoption and expert and evidence-based decision-making.

Pro-Clin:

A private company purchased the Pro-Clin system in 2002; it had been in use since 1988. The province of Kwa-Zulu Natal (KZN) is currently using this system, which includes modules for managing outpatient clinics, occupational health, HAART, inpatients, wards, theatres, accounts, dispensaries, 1.O.D. administration, diary menus, access security, and integrations and interfaces (DigiData, 2017).

ReMed:

According to the KZN Department of Health (2008), the ReMed Chronic Dispensing Programme is a web-based system developed by pharmacists from Pharmaceutical System Development. Speed and dependability were two important factors to consider when developing the application. Due to the database system's placement on the host institution's file servers, it can support a large number of users. A4 laser labels and thermal transfer labels are both available. Other features include "search" functions for patients, "queued prescription" functionality with clinic filter and date range options, password access control, and audit reports. Medication groups with frequently prescribed regimens organised for quick distribution, such as ARVs, are another feature. The developers and REM ED backup support have a service level agreement in place that limits response times to 24 hours.

Patient Administration and Billing System (PAAB):

Although the Patient Administration and Billing System (PAAB) is owned by the Department of Health, it is run by a private company. "Even though there is a module for recording clinical data, it is primarily used for administration and does not yet have the functionality to allow for integrated data use. In addition, the system currently lacks direct input of laboratory or radiological reports, an electronic interface to a pharmaceutical system, and decision support "(Wright et al., 2017).

Nootroclin:

Since January 2000, the Northern Cape Province has been using the Nootroclin HIS. Nootroclin is a "database agnostic solution which is now able to run on Oracle, lnformix, Cache or lnterbase (MindMatter, 2018). The Master Patient Index is one of the Nootroclin modules. Other modules include Order Entry, Results, ART monitoring, Diets, Theatre, Patient Registration, Inpatient Admissions, Outpatient Bookings, UPFS Billing, Debtors Management, Clinical Checklists, Pharmacy Management (NootroPharm Module), and Management Information. Standards supported by NootroClin include ICD-10 for diagnosis, NSN for pharmaceutical stock, and HL7 for interoperability with other systems (such as Disa*Lab).

Clinicom:

Nearly all hospitals in the Western Cape use the Clinicom system (Wright et al., 2017). According to Western Cape Government (2016) "The Clinicom system offers patients, doctors, and support staff a number of benefits, that include but are not limited to the following: When creating a single patient record, institutions can examine patient details and history; improved management of outpatient visits, including an automated system for scheduling outpatient appointments; and use of the Western Cape Patient Master Index by all Western Cape hospitals and Primary Healthcare Services ".

Primary Health Care Information System (PHCIS):

Since its implementation in 2006, the Primary Health Care Information System (PHCIS) has "linked 176 primary care clinics throughout the Western Cape province, managing EHRs of more than 5.2 million patients" (Chowles, 2014), and according to the Western Cape Government, facilities have reported the following benefits, (2016): "Coordinated and streamlined patient administration; Minimal duplication of patient information; Access to individual electronic patient records (EPR) via a unique patient number; Provision of an automated and more reliable headcount statistics; Improved service to patients; Reduced waiting times and time for patient admission; Improved communication."

JAC Pharmacy:

In the Western Cape, "pharmacy stock control, e-prescribing, and medicines administration as a single integrated solution" are offered by a different system called JAC Pharmacy (Mills, 2014). JAC is already present in more than 30 hospitals in the Western Cape, and it will soon be installed in the region's most important clinics (Mills, 2014). All of the systems previously mentioned are incompatible with one another because none of them are founded on a standard data definition or data dictionary. This problem hinders the information flow throughout the healthcare system. However, the absence of a common database management system (DBMS) makes it challenging to develop a master patient index.

The District Health Management Information System (DHMIS) Policy was developed by the National Department of Health and is mandated by the National Health Act, demonstrating the necessity of establishing a centralised medical information system in the South Africa National Health Act (Act 61 of 2003; Department of Health, 2014). Furthermore, the National Health Insurance (NHI) plan, which highlights the significance of medical information systems, states that electronic-based solutions must be a part of the system for the National Health Insurance (NHI) strategy to be successful (Department of Health, 2016).

In response to the requirement for interoperability, South Africa created a National Health Normative Standards Framework for eHealth (HNSF). The Department of Health and CSIR (2014) state that its primary objective is to establish the foundation for future interoperability. On the contrary the use of standards to guide the development of IT systems has several benefits, including alignment, integration, flexibility, portability, reuse, and a shorter time to market (Department of Health & CSIR, 2016). It follows that, the lack of uniform policies for the use of technology affects how decision-makers perceive the adoption of EHR in the healthcare sectors. As has long been recognised in the theoretical literature, different types of policy tools can have noticeably different effects on the pace and direction of technological advancement.

There is evidence that the use of interoperable HIT is growing (Furukawa, King, Patel, Hsiao, Adler-Milstein & Jha, 2014). Furthermore, using patient data for care delivery, quality enhancement, and public health promotion is becoming simpler (Rudin, Motala, Goldzweig & Shekelle, 2014). Inter-system health information exchange, also known as interoperable HIT, has drawn the attention of policymakers (Department of Health & Human Services, 2014). Interoperable HIT, however, can also be utilised to facilitate data exchange between systems within the same organisation (Braunstein, 2018). Its main objective is to specify the circumstances in which specific categories of information can be accessed (Furukawa et al.,2014). Health services deal with sensitive data and information, so policies are crucial. Maintaining the availability, privacy, and integrity of information resources is another goal of information security policies.

2.5 EVIDENCE-BASED PRACTICE IN PATIENT HEALTHCARE

Evidence-based practice has become increasingly important in recent years in international nursing practice (EBP). Numerous international studies have emphasised its importance of EBP (Saunders, Gallagher-Ford, Kvist & Vehviläinen-Julkunen, 2019; Shayan, Kiwanuka & Nakaye, 2019). It is referred to as "a continuous interactive process involving the conscientious and wise examination of available research evidence" in order to deliver better care (Yingfeng et al.,2020). Finding, retrieving, and applying prior knowledge based on research evidence in practice, as well as the daily accumulation of new knowledge and technologies, clients' shifting needs, and these issues are fundamental worries for nurses (Farokhzadian, Khajouei, Ahmadian & Farokh, 2015). The WHO (2014) states that the effectiveness of health systems depends heavily on nursing services, and that nurses' clinical decisions have a big influence on patients' well-being and treatment outcomes (Thorsteinsson, 2017). According to Zhao et al. (2017), the application of evidence-based practises benefits both nurses and patients. Healthcare systems are performing quite well despite current demands to cut costs and improve service quality (Leach, Hofmeyer, & Bobridge, 2016).

In an effort to demonstrate the quality of healthcare services and make responsible use of the resources available, the adoption of EBP has been repeatedly tried (Lau et al., 2016). The complexity of EBP has prevented its application in nursing even though it is widely acknowledged as a way to improve healthcare services for a variety of reasons (Saunders et al., 2016). One of the main obstacles to the adoption of EBP is the lack of information systems (IS) that permit a constant flow of patient data (medical and administrative data) throughout the therapeutic process. This is quite worrying, according to specialists (Iroju, Soriyan, Gambo, & Olaleke, 2018). A team of medical specialists, each of whom has a specialty, are rapidly replacing the traditional doctor-patient relationship. Contrarily, seamless, and shared care demands cooperation and quick information sharing among medical professionals (Iroju et al., 2018).

Research has specifically shown that factors limiting the scope of EBP include a lack of knowledge and skills, a lack of resources, a lack of support, a lack of financial, material, and human resources, as well as insufficient training in research methodology (Youssef, Alshraifeen, Alnuaimi & Upton, 2018). Furthermore, research has demonstrated that nurses' personal traits may occasionally affect how they view the elements influencing the implementation of EBP (Aburuz, Hayea, Al-Dweik & Al-Akash,2017; Skela-Savic, Pesjak & Lobe, 2016). There are few studies or data points available, though, to support this correlation. Some studies suggest that barriers to the adoption of EBP are related to nurses' professional experience and training (Aburuz et al., 2017, Park, Ahn & Park, 2015). Nurses do not have time to study because of their excessive workload. Evidence-based research is essential for improving clinical practices, boosting productivity, and helping healthcare professionals advance their careers (Strömberg, Aboagye, Hagberg, Bergström & Lohela-Karlsson, 2017).

a) Knowledge management integration in evidence-based healthcare

Knowledge is a vital advantage for performance in a culture built on knowledge. Knowledge starts with data, which are viewed as unprocessed raw facts. People look at these facts in a particular setting with a certain objective (Sanders, 2016). Akosile and Olatokun (2020) define knowledge as a higher structure of information that has been understood and applied. Knowledge enables an organisation to make informed decisions and adjust to changing external conditions. Businesses are paying more and more attention to organisational knowledge management because it has the ability to give organisations strategic results related to productivity and competitive advantage (Omotayo, 2015). Knowledge management (KM) is being used more and more in healthcare institutions due to the high reliance on information and evidence-based practise, as well as the large volume of knowledge that healthcare practitioners must manage (Wickramasinghe & Schaffer, 2017). Hospitals are knowledge-intensive environments that undergo ongoing change because of advancements in medical technology, claims Lee (2017). More knowledge resources are being created as a result, which calls for the employment of specialised equipment, advanced techniques, and skilled labour in the provision of healthcare.

In contrast to other organisations, hospitals are required to carry out a variety of processes, including healthcare provision, illness diagnosis and treatment, planning and implementation of admission procedures, medical interventions, and other processes, including making complex decisions within networks (Kieft et al., 2014). According to earlier studies conducted in developed countries, implementing a KM system in hospitals can enhance patient care, boost information sharing among healthcare professionals, enhance the therapeutic process, minimise healthcare expenses, and lower medical errors (Koushazade, Omidianpoor, & Zohurian., 2015). In the complex clinical settings found in hospitals, nurses play a crucial role in internal knowledge creation, information transmission, and knowledge updating (Salehi et al., 2015). According to earlier studies (Salehi, Mokhtar, Khademolhoseyni & Ebadi, 2015), nurses who are unable to demonstrate their knowledge proficiencies in clinical practice give patients poor care. The healthcare industry is always evolving; therefore, it calls for knowledge resources with higher levels of competence, aptitude, and methodology (Belay et al. 2021; Lee, 2017). The efficient management of knowledge in nursing practice is a key strategy for delivering high-quality healthcare. There are currently two types of knowledge reported in the literature: tacit and explicit (Dlamini, 2017; Awogbami et al., 2020).

b) Tacit knowledge

According to Dietel (2017), tacit knowledge is understanding that a person possesses but is unable to verbally communicate. Tactic knowledge is an elusive, abstract concept that is challenging for employees to convey through formal and informal discourse, narrative, or face-to-face involvement, according to Winter (2016) and others. As defined by Dietel (2017), tacit knowledge is context-dependent and passionately transmitted among people in a formal and systematic way. Jane (2016) asserts that tacit knowledge is particularly challenging to transfer from one person to another since it is deeply ingrained in the private lives of individuals, as well as those of co-workers and team members. In contrast to explicit knowledge, tacit knowledge is more challenging to retain, document, and embed in manuals, papers, and processes (Jane, 2014). Healthcare organisations, which are somewhat knowledge-intensive enterprises, employ numerous clinicians who are proficient in a wide range of disciplines. Professionalism is expressed and demanded by their ongoing upgrading of knowledge and technology, which is crucial for patient care, the calibre of healthcare services, and the reduction in medical errors (Yuan & Ma, 2022).

c) Explicit knowledge

Explicit knowledge is the form of knowledge that can be rapidly communicated in words, numbers, and concepts to communicate shared experiences, lessons learned, and relevance, according to Dietel (2017). Unlike tacit information, which lacks visual qualities, explicit knowledge can easily be recorded, stored, and codified for communicative reasons (Jane, 2016). Explicit nursing knowledge, as defined by the South African Nursing Council Assessment Report 2019, is the knowledge that possesses the most fundamental and key elements necessary in the process of providing services to patients. It is created, most importantly, through the encounter with a variety of rare diseases. According to Shaari et al. (2015), the particular type of knowledge that takes into account the science of providing services to patients gained through years of experience is what distinguishes them from other health professionals. Siu (2015) emphasises that the explicit nature of nursing knowledge is typically characterised by the caring nature of the nursing profession in general and the expectation crucial knowledge regarding patient care that has been accumulate through years of practises including the methods for providing services to patients to fitful the objectives of the healthcare sector.

2.6 eHEALTH SYSTEMS IN DEVELOPED AND DEVELOPING COUNTRIES

2.6.1 Developed countries

The state of eHealth varies as there is no one approach to implementing these systems globally. A literature study was undertaken to learn more about patient eHealth card records in developed countries, to understand what has been researched, how it has been researched and what is regarded to be significant concerns, particularly its reasons and importance. In this section, the eHealth care systems of Germany, Sweden and Australia which were selected randomly will be discussed.

i. Case Study 1: German healthcare system

In a comparison of healthcare systems around the world, the German healthcare system stands out because of its distinctive design and implementation of a self-governing healthcare system. Alternatively, it means that while the government creates the laws and regulations, the contributors to the system through insurance and other payments as well as the service providers organise themselves into a variety of groups to monitor the general public's access to healthcare (Brand & Hornuf, 2020). The foundation of the healthcare system is the Otto von Bismarck model which includes community ratings, universal insurance coverage and regulated private healthcare provision (Hendolin, 2021). Inpatient care (hospital sector), outpatient care (non-hospital sector) and rehabilitation facilities make up the traditional German healthcare system. In their individual offices, independent healthcare practitioners generally provide outpatient services. All citizens with insurance are given top-notch medical care via the hospital sector which include public, commercial and non-profit hospitals, and equipment. Public hospitals supply nearly half of all beds in Germany despite making up the smallest proportion of hospitals. In Germany, there are about 40 university hospitals that are both publicly and privately operated (Karmann & Roesel, 2017).

However, neither the federal states nor the required insurances provide private hospitals with any type of financial assistance or grant for investment. Patients are responsible for paying them back because private hospitals are funded through treatment agreements with them. The patients' respective health insurance companies then pay the patients back (Brand & Hornuf, 2020). With 376 billion euros (11.5%) of GDP spent on healthcare in 2017, Germany was one of the EU members with the highest healthcare expenditures (Statistisches Bundesamt, 2020). Mandatory contributions are split among three insurance schemes to maintain Germany's social health insurance system (Stroetmann, Artmann & Dumortier, 2018). Contributions, on the other hand, are made to government initiatives, private health insurers or statutory health insurers. Statutory health insurance plans are used to provide most of the insurance coverage. In addition, contribution obligations that are based on earnings are shared equally by the employer and the employee. According to Stroetmann et al. (2018), hospitals are managed by public, private or independent non-profit organisations and are under the control of state health authorities. Ambulatory medical care is provided by both general practitioners and specialists. Choosing a doctor, dentist, pharmacy, or emergency room is now easier for patients.

ii. Digital challenges in Germany's healthcare system

It has been demonstrated that digitisation in the healthcare industry has several benefits, some of which include personalised medicine, which facilitates system participants' communication, gives practitioners a deeper understanding of patients' health and empowers patients to manage their health through the use of apps and online resources (Pricewaterhouse Coopers, 2021). Among 17 countries, Germany came in second-to-last place in a global analysis of the healthcare industry's digital transformation (Bertelsmann Stiftung, 2018). The German government established a legal framework for the digitisation of healthcare in response to this lack of digitisation in the German healthcare industry. According to Lovell (2019) in November 2019, the "Act to improve Healthcare Provision through Digitalization and Innovation," also known as the "Digital Healthcare Act," (DVG) was passed. It paved the way for the digital transformation of the German healthcare industry, particularly with regards to electronic patient records, telemedicine, and e-prescriptions (Bundesgesundheitsministerium, 2019). Furthermore, the new DVG now provides a structured route for the reimbursement of digital health applications by statutory health insurance funds, making them widely available to patients.

It was anticipated that, by 2020, more than eight out of ten doctors would be connected to the telematics infrastructure provided by cloud systems, even though the majority of medical data will still be transmitted in analogy form. In solo practices and those that are highly specialised, like psychotherapy clinics, a higher percentage of patient information is also not digitalized. The outpatient sector is notable for having the lowest availability of digital offers because the majority of outpatient doctors do not offer alternatives for online appointment scheduling or prescription purchases through their websites (McKinsey & Company, 2020). Furthermore, doctors' resistance to the digital transformation of the healthcare industry is the main barrier to it. One justification for this fear is the reason for concern that it would damage the doctor-patient relationship. In addition, there are difficulties with data security and protection. Contrarily, most patients approve of using digital healthcare technologies (O’Connor, Mair, McGee-Lennon, Bouamrane & O’Donnell, 2016).

iii. Case Study 2: Swedish healthcare system

The 20 county councils in Sweden are responsible for managing the country's publicly funded healthcare system. There are both public and private primary care facilities. Every primary care facility is run by the government because every primary care facility is required to enter a contract with a county council that governs how healthcare market pricing is determined, (Burlacu & Roescu, 2021), Sweden offers affordable universal health insurance (The Swedish Institute, 2018). Thus, for a visit to a primary care facility, Swedish nationals are required to pay a predetermined fee that is a portion of the real cost. Sweden encounters a strong demand for healthcare services, similar to many other countries with universal health insurance (Ministry of Health and Social Affairs, 2022). Sweden has some of the longest waiting lists in all of Europe, according to Habibov, Auchynnikava, Luo and Fan (2018), which has long been a problem for the nation's healthcare system. Even though the best care available anywhere in the world is received, access and continuity of care problems still exist (Altman et al., 2018). Primary healthcare providers offer compassionate assistance and preventative measures in addition to basic medical care (Riksdagen, 2018).

Notwithstanding being legally defined, primary healthcare does not have a set standard for how it should be provided or organised. Instead, as was originally established, delivery is the responsibility of the county councils. Due to this, the county governments of different counties manage the primary healthcare system in different ways (Cavazza, Del Vecchio, Fattore & Fenech, 2023). Elderly healthcare in Sweden is the responsibility of local governments (Swedish Government, 2020). Moreover, there is change in the Swedish healthcare system. Numerous legislative measures are currently under progress at the international, national, and regional levels to authorise or promote safe and effective instruments for patients to take control of or at least participate in their own care. Standards for the design of software as medical devices, updates to medical device directives and new regulations on collaboration that outline how publicly funded health care providers should work with their suppliers are a few examples. According to a study on the matter, it is critical to consider how policies are carried out at the various levels of the health care system (Balen & Leyton, 2018).

iv. Digital challenges in Sweden's healthcare system

Patients can still be empowered even if technical advancements in healthcare are only seen to an end, claim Schartinger, Miles, Saritas, Amantidou, Giesecke, and Heller-Schuh (2017). Based on her knowledge of the industry, Ostlund (2017) outlined the difficulties associated with digitising healthcare in Sweden. For the digitalisation of healthcare to be successful, she emphasised the necessity for proactive and collaborative efforts as well as the active involvement of senior users. She also emphasised how, particularly when it comes to older people, criteria are sometimes not reviewed with actual end users. In addition, she went on to argue that it is crucial for the healthcare industry to overcome the difficulties presented by digital surroundings if it is to fully appreciate the consequences of digitisation in a controlled setting that is more like the real world.

Barkman and Weinehall (2017) analysed the influences and mobile healthcare in Sweden, Ghana and Ethiopia in comparative research. Despite having a highly developed system, the researchers claim that Sweden has some problems such as the integration of health data, the use of digital decision support to generate individualised medications, future funding and the efficiency and quality of healthcare systems. Focus group interviews were done by Oberg, Orre, Isaksson, Schimmer, Larsson and Hornsten (2018) to gain insight into the attitudes and concerns of Swedish primary healthcare nurses towards the adoption and usage of digital healthcare systems. In addition, nurses were concerned about the prospect of an increase in their operational responsibilities as well as the need to adopt new practices and policies connected to digital healthcare. According to the study's findings, nurses urgently need education and training to take part in the implementation of eHealth. The expectations of respondents for remote monitoring and automation have grown, according to a 2019 survey of Swedish home care nursing providers (Rydenfält, Persson, Erlingsdottir & Johansson). Grindrod, Li, and Gates (2018) further highlighted that usability issues and systems' incapacity to adapt to the usage context were the key implementation obstacles.

Furthermore, the healthcare system faces a variety of adoption difficulties, such as resistance from professional and organisational levels, unfavourable accounting systems, difficult purchasing practices, a lack of accountability and incentive, among many other problems (Schartinger et al., 2015). The complexity of the healthcare system is increased by the fact that different clinics employ new technological advancements in various ways and by the presence of numerous complicated and competitive forces operating at various levels (Krohwinkel et al., 2019). Tragically, this suggests that patients may not be receiving treatment that takes advantage of recent scientific advancements and technological innovations that have been shown to be beneficial.

Case Study 4: Australian healthcare system

The Australian federal and state governments collaborate to manage the healthcare system. Decision-making and intergovernmental collaboration take place at the Council of Australian Governments (COAG), Australia's premier intergovernmental body (Mossialos, Wenzel & Osborn, 2016). Currently, Medicare is a federally financed public health insurance that provides a range of free or reduced health services to Australians (Mossialos et al., 2016). Australia's healthcare system is made up of two divisions (Wickramasinghe, Fadlalla, Geisler & Schaffer, 2015). In other words, it consists of two separate parts: public hospitals and private hospitals, each with a different variety of financing options. With six states and two territories, Australia makes it challenging for the government to control the healthcare systems. Hence, the financial and healthcare systems of Australia are a convoluted amalgam of private and public services. In 2016, Australia allocated 10.3% of its GDP to health. Australia's national healthcare system is called the Medicare Benefits Scheme (MBS) (Australian Institute of Health and Welfare, 2017). Medicare levies of 2% of taxable income for those who earn more than a certain level help to partially finance the MBS.

General practitioners (GPs), specialists, and a comparatively small number of allied health services are all covered by the MBS. Many doctors incur additional expenses on their own dime known as "gap charges." Rising medical costs since the MBS's launch have increased consumers' out-of-pocket gap payments because MBS subsidies were not recorded (Duckett, 2016). Many primary care services are provided by general practitioners in private practice. MBS pays for doctor visits using a time- and complexity-based payment structure. In regions where a commercial model is impractical, state health authorities or nongovernmental organisations (like the Royal Flying Doctors Service) may provide general practitioner services using salaried doctors (such as in remote settlements). Acute care services that are owned and run by state and territorial governments are jointly funded by the Commonwealth Government and the State or Territory Governments. One common name for it is "the public hospital system."

Activity-based funding (AFB) is a source of support for acute hospitals. However, hospitals that are unable to function within an ABF model use block financing. Australia has most of its emergency rooms in public hospitals. In addition, many Australians have private health insurance (Duckett, 2016). Private health insurance typically pays for private hospital admissions, private allied health services, and private dental care. If an Australian citizen's annual income falls below a certain level, they are entitled to a 30% discount on the cost of private health insurance. According to Australian Medical Association (2018), anyone in Australia over 30 without health insurance is currently subject to tax penalties. Despite incentives, the number of Australians with private health insurance is currently declining. Private health insurance coverage for hospital admissions decreased from 50% in 1984 to 47.4% in 2015 and 46.5% in 2017 (Australian Medical Association, 2018; Briggs, 2017).

v. Digital challenges in Australia's healthcare system

To improve consumer and healthcare professional access to patient medical records, the Australian government started the transition from paper-based records to electronic health records (EHRs)] (Hall, Fiebig & van Gool, 2020), According to Australians Institutions of health and welfare (2020), the country is ranked ninth internationally for the use of EHR. The Australian healthcare system is also renowned for offering excellent care and is among the best in the world. Even though the Australian healthcare system is more organised, there are not as many open access options (Behera, Behera, & Satpathy, 2020). In addition, the aging population, rising prevalence of chronic diseases, rising patient demand for more costly, sophisticated, and technologically advanced procedures, and a concomitant shortage of skilled healthcare workers have all contributed to Australia's healthcare system becoming significantly more expensive and complex (Purohit, Smith & Hibble, 2021).

Furthermore, Australia still lacks the legal framework and infrastructure needed to run its national eHealth platform. According to the Australians Institutions of health and welfare (2020) the platform currently only serves 11% of Australia's population and just over 8,000 healthcare provider groups, the majority of which are general practices. Australian Medical Association (2017) usage rates have not yet reached the threshold required for full adoption of eHealth services due to a lack of legislative enforcement to adapt the platform for things like billing or insurance claims. The Personally Controlled Electronic Health Record (PCEHR) system was renamed to My Health Record in 2016 and added an opt-out option due to a lack of meaningful use. Increased system acceptance is expected to increase the system's value to healthcare professionals and encourage them to use it. It is important to minimise barriers to registration, especially for healthy individuals and patients who are in need (Willis & Parry, 2016).

2.6.2 Developing countries

A literature study was undertaken to learn more about eHealth and electronic health records systems in developed countries, to understand what has been researched, how it has been researched and to understand what is regarded to be the significant concerns, particularly its reasons and importance. In the following section, the eHealth care systems of Ghana and Kenya which was also selected based on random sampling will be discussed.

i. Case Study 1: Ghanaian healthcare system

Ghana, a West African country with a lower middle class, became the first African nation to be freed from British rule in 1957. A population of over 30 million people, including 13% who live in poverty on less than $1.90 per day and 43% who are thought to live in rural areas, is estimated for Ghana by the WHO, OECD, World Bank (2018). Malaria and other diseases linked to poverty remain the main causes of death in Ghana (IHME, 2017). Ghana is one of the few nations in Africa where the National Health Insurance (NHI) law governs the healthcare system (Akum, 2014). Moreover, since the country's independence in 1957, the government has provided free healthcare. Furthermore, the Ministry of Health is the main administrative body in charge of all matters relating to health (MOH). It aims to make high-quality medical care available to all Ghanaians. In order to provide a healthy and productive population for socioeconomic development and eventually, national development, the MOH promotes health and vitality. The Ministry of Health (MOH) is responsible for, among other things, organising and allocating resources to all service providers, monitoring, and assessing Ghana's health service quality, and providing general policy direction to all parties involved in the delivery of health services (Ministry of Health, 2014).

Implementing healthcare regulations and overseeing government healthcare initiatives fall under the purview of the ministry-affiliated organisation known as the Ghana Health Service (GHS). Despite these obligations, a different government agency oversees overseeing the development of a healthcare system that is more flexible, open to all, effective, and egalitarian across the country. This rule does not apply to teaching hospitals, private hospitals, or mission hospitals that are directly supervised by the MOH. GHS oversees offering comprehensive and easily accessible health services with a focus on primary healthcare at the regional, district, and sub-district levels. The GHS is in charge of managing and administering the service's overall health resources in order to promote, protect, and restore Ghana's health (Ministry of Health, 2014). Several sources provide funding for the National Health Insurance System (Alhassan, Spieker Nketiah-Amponsah, Arhinful & Rinke de Wit, 2016). Alhassan et al. (2016) highlighted that, the insurance system is financed in part by the National Insurance Trust, a small portion of Social Security, and taxes on goods and services. Furthermore, the National Health Insurance System also receives funding from premiums, donations, grants, contributions, gifts, and investment interest, according to Alhassan et al. (2016). The funds raised are also used to support the NHIP's health insurance programs (Ministry of Health, 2014).

Ghanaians can choose from three different National Health Insurance Program (NHIP) health insurance plans (Ministry of Health, 2014). The three health insurance programs are District Mutual Health Insurance Schemes (DMHIS), Private Mutual Health Insurance

Schemes (PMHIS), and Private Commercial Health Insurance Schemes (PCHIS)] (Ministry of Health, 2004). To enrol residents in the DMHIS, each district must establish a health insurance program (Ministry of Health, 2016). This neighbourhood-based, non-profit health insurance program is decentralised (Ministry of Health, 2014). If there are any year-end surpluses, the health insurance programme will maintain them and use them to reduce rates or enhance benefits (Ministry of Health, 2016). The District Mutual Health Insurance Scheme is sponsored by public money, according to the Ministry of Health (2016).

ii. Digital challenges in Ghana's healthcare system

In Ghana, very few eHealth studies have been conducted. Nevertheless, some studies have been conducted on the readiness of developing countries for eHealth such as those by Yusif and Soar (2014); Mugo and Nzuki (2014) which examined a section of the deployment of eHealth in Ghana within the context of developing countries, more generally. Since 2010, Ghana has had a national eHealth plan that serves as a development roadmap for the country 's public healthcare system. To increase the quality of healthcare delivery services offered to its population, Ghana created an electronic healthcare system known as eHealth Care (Acheampong, 2012). Due to obstacles such as a lack of experienced employees, the high cost of equipment, a lack of finance and the difficulty of translating paper-based information into electronic format, the acceptance and deployment of EHR systems in Ghana have been delayed (Kiberu, Mars & Scot, 2017; Banshanga & Ejiri, 2016). Ghana has also had difficulty utilising EMRs due to a variety of problems, such as a lack of funding, human resources, and coordination for the implementation of EMRs (Da-Costa Vroom, Godia, Derya & Afagbedzi, 2017).

Two of the issues that Ghana's healthcare system faces are a shortage of appropriately trained medical personnel and subpar infrastructure. Ghana, like many other underdeveloped countries, has a poor doctor-to-population ratio. In 2010, there were 1.14 nurses for every 1,000 persons and 0.11 doctors (Bedeley & Palvia, 2018). Power outages may damage data and result in a partial or complete program failure because EHRs are dependent on physical hardware (Patkar, Price & Lee, 2016). Due to a lack of infrastructure, it is difficult to provide people with the high-quality healthcare and patient advocacy they require. Patients who get poor customer service or a lack of empathy may feel more vulnerable and decide to self-medicate rather than seek medical attention, which can also lead to a breakdown in safety and communication (Moudatsou, Stavropoulou, Philalithis & Koukouli, 2020).

Furthermore, most Ghanaian professionals lack the essential ICT skills necessary to produce reliable EHR findings (Bedeley & Palvia, 2018). However, this is partially explained by the traditional Ghanaian way of life. Many Ghanaians who are still alive today spent most of their childhoods in rural areas without electricity or access to computers, so there is less of an eHealth adoption among rural residents and medical professionals. In developing countries with healthcare personnel who have received ICT training, awareness of and acceptance of eHealth are relatively high, as is actual use (Rudolph, Raemer & Simon, 2014). Patients might become more resistant because of modifications to accepted medical procedures (Acquah-Swanzy, 2015).

iii. Case Study 2: Ugandan healthcare system

The provision of healthcare services in Uganda is decentralised from the national level to the levels of referral, district, health sub-district, sub-county Health Center III, parish Health Center II, and village/cell Health Center I, with the latter being the lowest level and involving village health teams and volunteers who promote health and encourage community participation and empowerment (Nakisozi, 2014). Uganda's healthcare system currently consists of the primary, secondary, 48 tertiary, and quaternary systems. Primary healthcare at its most fundamental level is provided through hospitals and clinics. Local general referral hospitals provide tertiary medical services. National referral hospitals, namely Mulago and Butabika, provide quaternary healthcare. In addition, general hospitals and Health Centers 1-1V serve the entire original and old 39 districts (as of 1992). Nabukera (2016), further highlighted that, a health facility is within ten to five kilometres of 27% and 57%, respectively, of the population of Uganda.

According to the Ministry of Health (MOH)-A, 2019), the Kabale Regional Referral Hospital receives patients from Uganda's neighbours Rwanda and the Democratic Republic of the Congo. Uganda's health sector developed the Health Sector Integrated

Refugee Response Plan to coordinate the nation's response to the expanding refugee population and host communities (HSIRRP). "Universal Health Coverage for All" is its catchphrase (MOH-B, 2014). The Ministry of Health, in collaboration with other National Level Institutions, oversees the hierarchy of National Referral Hospitals (30,000,000 population), Regional Referral Hospitals (2,000,000 population), District Health Services (District level, 500,000 population), Referral Facility-General Hospital (District level, 500,000 population), or Health Centre IV (County level, 100,000 population) (Mukasa, 2016).

iv. Digital challenges in Uganda’s healthcare system

Uganda has been utilising modern health technologies like telemedicine, electronic medical records, and medical informatics to improve the delivery of healthcare services (Kiberu, Mars & Scott, 2017). Implementing such technologies has not been easy, though, because of context-specific problems like a lack of funding, computer illiteracy, and a lack of healthcare infrastructure. In developed countries like the United States, Australia, and the United Kingdom, public health spending is rising (Fisk, Livingstone & Pit, 2020). It is strongly encouraged and supported to develop comprehensive, effective health information and communication technology (ICT) systems (Patel & Kannampallil, 2014). On the other hand, underdeveloped nations face many difficulties in the management and delivery of healthcare services, including a lack of funding, a lack of computer literacy, and inadequate infrastructure.

Despite the implementation and recording of numerous eHealth initiatives (Fanta, Pretorius & Erasmus, 2016), useability problems with eHealth systems in developing countries have grown to be a growing cause of concern (Nahurira, Businge & Nakato, 2016). Complicated system user interfaces, a dearth of interactive eHealth systems and privacy and security concerns are some of the challenges (Sahi, Lai & Li, 2016). Vélez, Okyere, Kanter and Bakken (2014) claim that the absence of user involvement in the design process, the system interfaces' poor design and the misalignment of eHealth interventions with user needs are all to blame for the useability problems. The development of eHealth at all levels has received huge resources, yet this has frequently resulted in the collapse of eHealth systems and the construction of long-term unsustainable systems (Nahurira et al., 2016).

Uganda has created scalable eHealth services despite its current problems. To increase internet penetration, the country, like other countries in Africa, has implemented 3G and 4G broadband internet services (Shuaib, Suarez, Romero et al., 2016). It should be made clear that the lack of 3G and 4G services in the majority of rural areas is a result of the residents' inability to afford them. It has also been shown in the literature that, another issue currently plaguing the healthcare sector is the brain drain brought on by a lack of skilled healthcare professionals (Manyisaa & Aswegenb, 2017). These health professionals' migration from rural to urban areas within a single country as well as from developing to industrialised nations are examples of the brain drain phenomenon. Ghana and other developing countries fall short of the World Health Organisation's (WHO) recommendation that there be 10 health workers for every 10,000 people (Oluoch, Muturi, Kiriinya, Waruru, Lanyo, Nguni, Ojwang, Waters & Richards, 2018).

2.6.3 eHealth systems in developed and developing countries

The eHealth landscapes of rich and developing nations are very different, and this digital fraction is evolving into a digital split (Shuvo, Islam, Hossain, Evans, Khatun, Ahmed, Gazi & Adams, 2016). Poor or ambiguous eHealth strategies are a major impediment to effective investment, deployment of sustainable eHealth solutions, and creation of an eHealth-friendly policy environment in many developing countries (Katehakis & Kouroubali, 2019). Information technology could significantly enhance a number of areas and benefit both developed and developing nations (Shuvo et al., 2016). Electronic health record (EHR) systems are increasingly being adopted by both developed and developing nations (Tilahun & Fritz, 2015; Krousel-Wood, McCoy & Ahia, 2018). Electronic health record systems (EHRs), which store and securely transfer clinical data across several authorised users outside of one provider's office, are different from electronic medical records (EHR), which are a repository of patient data in digital form within a single practise (Capurro, Yetisgen, & van Eaton, 2014).

EHR adoption rates have risen swiftly in affluent nations, but slowly in less developed ones where they are mostly employed for administrative goals rather than therapeutic ones (Odekunle, Odekunle, & Shankar, 2017). EMRs have been used in the US for more than 30 years; between 2014 and 2017, the percentage of hospitals with EHR capabilities increased from 58.9% to 80.5% (Adler-Milstein, Holmgren, Kralovec, Worzala, Searcy & Patel, 2017). More than 90% of the time in Australia, general practises use electronic medical records in some capacity (Adler-Milstein et al., 2017). Continuous efforts to improve health in developing nations like South Africa, Uganda and Ghana progress has been hampered due to dysfunctional health systems that are unable to provide high-quality, affordably priced healthcare to populations in need (Granja, Janssen & Johansen, 2018). Lack of legal and policy frameworks, a lack of health workforce, and geographic and financial barriers to healthcare are all problems that developing countries face when it comes to their health systems (Kruk, Gage, Arsenault, Jordan, Leslie, Roder-DeWan, Adeyi, Barker, Daelmans, Doubova, English, García-Elorrio, Guanais, Gureje, Hirschhorn, Jiang, Kelley, Lemango, Liljestrand, Malata, Marchant, Matsoso, Meara, Mohanan, Ndiaye, Norheim, Reddy, Rowe, Salomon, Thapa, Twum-Danso & Pate, 2018). These challenges make it difficult to deliver health services to those who need them effectively. The importance of using digital technology to provide health care in undeveloped countries has gradually risen on the global public health policy agenda over the past 15 years (Kruk, et al., 2018).

In several developed countries, primary care providers use EHR at a rate greater than (50%) of the total. Sweden, Germay and Australia are among those with respective utilisation rates of 90%, 62%, and 55% (Mugo & Nzuki, 2014). In other wealthy, stable economies, technology is widely used, but eHealth seems to be doing much worse. According to the National Centre for Health Statistics (2015), different states have different percentages of clinicians using EHR systems, ranging from (54%) in New Jersey to (89%) in Massachusetts. Research demonstrates that nurses in these countries do not keep up with technological innovation, which is why developing countries have difficulty implementing eHealth systems due to inadequate eHealth infrastructure (Cetin, Ergün, Tekindal, Tekindal & Tekindal, 2015; Okeyo, 2016).

In addition, the improper integration of informatics in nursing, inadequate computer literacy, resistance to change, resource limitations, limited access to the internet and slow internet speed, and a lack of information-searching skills are just a few of the problems that have hindered the development of ICT skills among nurses and nursing students (Bello, Hassan, Yunusa, Abdulrashid, Usman & Nasidi, 2017). This demonstrates that other issues, like a lack of technical support in healthcare institutions and inadequate ICT training among health professionals, are just as important for the deployment of eHealth systems given the current state of eHealth globally. Therefore, it is essential to contextualise rather than generalise the factors that affect how eHealth is used.

Furthermore, because of infrastructure problems like unstable power and inadequate internet connectivity, the country has struggled to develop and implement effective health information systems (Seitio-Kgokgwe, Gauld, Hill & Barnett, 2015). According to Ben-Assuli (2015), many European and American countries have adopted EHR and electronic prescribing systems slower than anticipated. Implementing eHealth is frequently costly and prone to delays. The adoption of innovations in the healthcare sector may be hampered by personal, institutional, or systemic problems (Sugarhood, Wherton, Procter et al., 2014). Alkhater, Wills, and Walters (2014) claim that businesses may be hesitant to adopt a particular technology because there are no laws that can shield organisations in the event where data is compromised.

Innovation in the healthcare industry is more difficult than it is in the consumer products industry because of these pressures and the inherent characteristics of the sector. A fully committed and supportive top management is necessary for the successful adoption of technological innovations, according to research by Lee, Shiue, and Chen (2016). Currie and Seddon, (2014) further noted that, numerous financial, legal, social, and ethical implementation barriers also exist at the organisational and individual levels. Inadequate eHealth literacy, security concerns, user ignorance of benefits, a lack of cost-effectiveness evidence, and interoperability (the ability of various information technology systems and software applications to communicate, exchange data, and use the information that has been exchanged) are some of these barriers (Currie & Seddon, 2014;

Stroetmann et al., 2018). It is important to understand barriers and facilitators for the development of strategies and treatments that will enhance the widespread effective use of eHealth and remedy the implementation issues.

2.7 eHEALTH CHALLENGES IN DEVELOPING COUNTRIES

This section will discuss some of the obstacles to eHealth adoption and implementation.

2.7.1 Lack of funding to implement eHealth systems

The cost of EHR implementation is one of the most frequently mentioned barriers to adoption, according to Odekunle et al. (2017). For those who can afford it, the cost of computerised equipment in most hospitals in developing nations may be more prohibitive; the practice of routine maintenance is another expensive issue to handle (Kanyua, 2015). Anyango (2017) investigated the problems with Nairobi's EHR systems and found that the expense barrier was a significant barrier to EHR investment (Anyango, 2017). However, studies indicate that failure to adopt HIT systems may result from subpar HIT design, subpar clinician use of HIT, or socio-organisational factors such as goal conflicts, a lack of time, or a lack of support from co-workers (Beckers Health IT, 2016).

However, it is unclear what measurements were used in these studies (Odekunle *et al.,* 2017). The inability to distinguish between technological and human components while implementing HIT systems technology limits the relevance of research findings (Vessey & Ward, 2013). In addition, this technology may not be implemented due to the high initial cost of establishing HIT systems and the length of time needed for adoption that has a negative impact on productivity and patient happiness (Tall et al., 2015). There is conflicting research demonstrating that EHRs can reduce healthcare costs (Sadoughi, Khodaveisi & Ahmadi, 2018). Although 50% of studies indicate the financial advantages of HIE deployment, several studies in their systematic evaluation cited HIE's cost-effectiveness as non-significant (Sadoughi et al., 2018).

Implementing a complete EHR system could cost a large health care organisation several billion dollars or more (Beckers Health IT, 2016). Many healthcare systems report significant implementation and maintenance cost overruns, and the maintenance costs of these systems could reach several hundred million dollars annually (Cohen, 2017; Resneck, 2018). According to a survey, purchase expenses is the main barrier to EHR adoption for 74% of non-adopters and 51% of adopters (Jamoom, 2014). However, long-term financial advantages can easily outweigh up-front expenses. For maintenance and failure prevention, the eHealth care system's funding source is crucial (Rudolph et al., 2016). In larger hospitals, resource and information use can be more effectively utilised throughout the organisation.

Numerous studies have found a favourable correlation between ICT availability and organisation size, likely because larger hospitals have more resources than smaller organisations like clinics (Mugo & Nzuki, 2014; Pawar, Parolia, Shinde, Edoh & Singh M. 2021; Noh, Im, Kim, Kim Kwon & Cha, 2021). It is difficult to allocate sizable sums toward the purchase of necessary ICT resources due to the health industry's limited financial resources. Many developing countries' healthcare systems require more funding due to the high cost of establishing computerised health infrastructure. Increased investment in the healthcare sector is closely related to the adoption of eHealth. It is essential to remember that only a select few institutions are guaranteed public funding, with the amount allocated to a particular health institution corresponding to its size (Rudolph et al., 2016).

2.7.2 EHR rollout and a lack of internet access

Telecommunications infrastructure greatly facilitates the transmission of health information between healthcare organisations, between healthcare organisations and patients and between healthcare organisations, patients and outside parties like insurance companies. If communications and internet penetration are low, the relationship between patients and healthcare facilities suffers (Mugo & Nzuki, 2014). Infrastructure for eHealth has a significant impact on how widely it is used because hospitals in remote areas are required to have internet access (Rudolph et al., 2014). The capacity of a country to connect to the internet is essential to its development and many African regions are gradually improving (Oyeyemi, Gabarron & Wynn, 2014). However, it is not widely used due to recurring power outages, lost internet access and a lack of qualified medical workers (Kiberu, Matovu, Makumbi, Kyozira, Mukooyo & Wanyenze, 2014).

Internet-enabled technologies can promote behavioural change and give people the power to knowledgeably decide on their health. As a result, they may stimulate demand for medical services. For instance, having access to online information may improve prenatal care and promote safe deliveries (Abekah-Nkrumah, Guerriero, & Purohit, 2014). However, low internet connection speeds and capacity are two of the biggest barriers to the adoption of Electronic Health Records (EHR) in many developing countries, claim Muchangi and Nzuki (2014). For instance, a lack of internet capacity is the main problem in Africa. The internet serves as the foundation for the development of the numerous EHR apps. For data-transmitting amenities, telemedicine, and access to health information, the internet is necessary (Muchangi & Nzuki, 2014). A dependable, quick internet connection that can improve data recovery and transmission is necessary for regular use of EHR (Rosenbloom, Carroll, Warner, Matheny & Denny, 2017).

Despite numerous studies that clearly demonstrate the advantages of electronic health, adoption of the technology is still low in underdeveloped countries, with slow internet connections serving as the main barrier (Muchangi & Nzuki, 2014). However, internet connectivity is a major problem in Ghana and other underdeveloped countries (Rudolph et al., 2016). According to the South African National Integrated ICT Policy (2016), South Africa lacks the high-bandwidth networks necessary to successfully deliver healthcare. In addition, there are restrictions on internet capacity and access in poor countries, especially in rural areas. The adoption of electronic health records (eHealth) will lag behind in wealthy nations with high implementation rates, like Denmark, according to Rudolph et al. (2016). It is crucial to remember that there are various network infrastructure issues that vary by region and service provider.

2.7.3 Unstable power supply and EHR adoption

Dependence on hydropower is one of the most important aspects of sustainable development in sub-Saharan Africa (Falchetta, Gernaat, Hunt & Sterl, 2019; Cole, Elliott & Strobl, 2014). Many countries lack accessible means of responding to brief disruptions brought on, for example, by hydro-climatic extremes like a delayed rainy season or anomalous periods of drought and flooding. Independent power producers' diesel backup capacity is frequently too expensive to fully make up for the momentary loss in hydro generation (Karekezi, Kimani, Onguru & Kithyoma, 2012). As a result, brownouts, blackouts, and load shedding are frequent. Recent reports of disruptions due to drought include, for example, Kenya, Malawi, Tanzania, Ghana, Zimbabwe, and Zambia. These reports include frequent outages, power rationing, unfavourable business experiences, and loss of competitiveness during precipitation anomalies (Gannon et al., 2016).

Since 2008, rolling blackouts have plagued South Africa because of Eskom, the company that supplies most of the the country's power, being unable to keep up with demand with its outdated and poorly maintained plants (BusinessTech, 2022). Network failure was noted as one of the frequent issues with clinical information systems in a study by Ahmadian *et al.* (2017). The unstable power supply causes system failures make it impossible to enter data or access information from HIS and places a burden on health workers who must manually collect data to later enter into the systems. Hospital downtime can occur for four different reasons, per a 2019 study by Chen, Chindarkar, and Xiao (2019), 69 to 100% of downtime events were attributed to network problems, which also included power outages brought on by human error, standby power failures, and power failures caused by the supplier. Software errors, a partial or complete loss of EHR software functionality, and other common causes can all lead to a system that responds slowly or is unavailable to end users.

According to Ash, Berg and Coiera (2018) system interface failure may occur if the EHR is linked to another system that has an impact on it directly or indirectly. Two excellent examples are the radiology imaging system and the laboratory information system. If one of these systems is unable to connect to the primary EHR due to the lack of results, patient care is delayed. Patient safety and treatment continuity are in danger in the healthcare sector due to computer system breakdowns. A patient's medical record, which includes details on their family, present and past health conditions, and treatment goals, is comparable to their personal history. Due to lost data and corrupted files, power outages can harm IT systems, hinder clinical workflow, and even result in death among patients

(Chen et al., 2019). Healthcare and other important industries are in danger of collapsing, according to Middleton, Bloomrosen, and Dente (2017), Karsh, Weinger, and Abbott (2018) since the supply of power in developing countries is not keeping up with its demand.

2.7.4 Resistance to change among healthcare professionals

One of the biggest difficulties is getting clinicians to use HIT technologies. IT systems have many flaws, and it has been examined why clinicians dislike or fear technology (Ayanso, Herath & O'Brien, 2015). According to Sebetci (2018), user intentions are closely tied to how satisfied they are with the EHR. Users' intentions to utilise technology are influenced by a variety of factors, including performance expectations, enabling conditions, and social pressure (Adenuga, Lahad, & Miskon, 2017). Previous studies on hospital staff attitudes and EHR usage have yielded a wide assortment of conclusions. Despite differences in the state and anticipated use of EHR capabilities, most doctors who responded (about 80%) agreed that using EHRs should raise the standard of care (Emparanza et al., 2015). According to Hossain's 2019 study, doctors' opinions of the risk that EHR present affected their choice to use the system. The use of EHR in medical practices causes significant upheaval for doctors who have established work habits, especially in terms of control over business/organisation operations and their relationships with patients. If doctors believe that the restrictions and guidelines of the systems limit their autonomy and adversely impact their interactions with patients, they are less likely to use EHR.

A South African study found that the adoption of dual eHealth information systems (EHIs) was challenging due to clinicians' opposition to using the system and preference for a paper-based approach (Ohuabunwa, Sun, Jubanyik & Wallis, 2016). The main challenges to the effective implementation of hospital based EHIs in Iran are the system developers' unfavourable perceptions and lack of acceptability (Ahmadian, Khajouei, Nejad, Ebrahimzadeh & Nikkar, 2014). Hospital administrators in South Africa are reluctant to use the EHIs, even though it provides vital information, because they have a negative attitude toward using it (Marutha & Ngoepe, 2017). In a state of readiness review for rural South African communities, the intervention was mostly rejected due to resistance to change and unfavourable views, according to Kgasi & Kalema's (2014) study on EHIs. Any prospective EHIs initiatives must deal with these issues to be successful (Kgasi & Kalema, 2014).

Hossain, Quaresma and Rahman (2019) did a cross-sectional survey study to evaluate the intentions of 300 clinicians working in both public and commercial healthcare facilities in Bangladesh toward EHR. According to Hossain *et al.* (2019), factors such as social influence, enabling circumstances, and individual creativity were found to have an impact on the adoption of EHR. Furthermore, the authors set out to confirm resistance to change's impact on behavioural intention after identifying it as a critical success factor for EHR adoption. The sample's failure was explained by pointing out that older people are more likely to experience resistance (Hossain et al., 2019). Since the desire to succeed is the primary motivation in the change process, the human element of change is at the centre of successful change management planning. Consequently, Al-Moosa and Sharts-Hopko (2016) argue that change implementation depends on the organisation and its staff's willingness to adapt. However, the biggest challenge with change is the requirement for people to modify their working practices.

Furthermore, most of the change occurs on an individual basis; change cannot occur in a group or organisation unless all members actively accept it. Without human change, no amount of project management, vision or solution will be successful (Prosci, 2020). To manage change on a human and organisational level and to enable a smooth transition, new change models, frameworks, and tools are needed (Prosci, 2020). Users' attitudes, requirements, and expectations have an impact on why they choose to utilise technology. In addition, users of health management information systems (HMIS), such as nurses, office workers, hospital administrators, patients, and other stakeholders, may have different preferences for these (Handayani, Hidayanto, Pinem, Hapsari, Sandhyaduhita & Budi, 2017).

2.7.5 Lack of system interoperability in public health institutions

Despite being collaboratively connected, healthcare institutions currently deal with healthcare systems that function in silos. EHR systems streamline data management and information sharing while also enhancing the functionality of current systems. The study also highlights the value of electronic medical records (EHR), which are utilised in healthcare for diagnosis and treatment and contain particularly sensitive private information (Dubovitskaya, Xu, Ryu, Schumacher & Wang, 2017). This information "must be regularly provided and shared among healthcare professionals, insurance providers, chemists, researchers, and patients' families, among others" (Dubovitskaya et al., 2017). According to experts (Greer, 2015; Jacob, 2015), all stakeholders should have unrestricted access to EHR data repositories. Other researchers (Plantier, Havet, Durand, Caquot, Amaz, Biron & Perrier, 2017) have questioned the ethical ramifications and security dangers of this type of access. According to medical professionals, for them to have access to patient medical records and manage patient health data, a change in the information-sharing paradigm and increased interoperability are both necessary (Lee, Dy, Gurses, Kim, Suarez-Cuervo, Berger, Brown & Xiao, 2018; Finset, 2018).

Insufficient connectivity further reduces the efficacy of HIT projects in South African public hospitals by making communication and information retrieval difficult (Mostert-Phipps, Pottas & Korpela, 2016). Mchunu (2017) claims that the amount of data that can be shared across the Clinicom and PHCIS systems in South Africa, for instance, is constrained by users' inability to freely communicate data between them. Interoperability, according to Riso, Tupasela, Vears, Felzmann, Cockbain, Loi, Rakic et al. (2017), can promote service transparency by making data accessible to all stakeholders, fostering more fruitful interactions, providing access to extensive information stored within the system, and significantly increasing jurisdictional sharing of healthcare information and services.

Zimbabwe uses electronic systems to create and maintain medical and health records for patients at the departmental and institutional levels, but it does not appear that these systems are coordinated and standardised to allow for meaningful sharing of health information among the country's healthcare facilities (Mutsagondo & Tsvuura, 2017). The country's healthcare sector is unable to completely implement such computerised solutions because there are no standards for these systems (Mutsagondo & Chaterera, 2016). Since a large portion of the technology utilised in Zimbabwe's healthcare system was created particularly for each facility, compatibility problems are commonly encountered (Furusa & Coleman, 2018). In their 2017 article, Abid, Keshavjee, Karim, and Guergachi lamented the difficulties of the lack of interoperability between EHR and EHR systems and noted that such technologies in healthcare institutions like hospitals and clinics tend to operate independently from one another so that data is preserved in silos. The problem has been made worse by the fact that data entry screens and templates are typically kept in offline silos (Abid et al., 2017). Interoperable systems that promote communication between local health departments (LHDs) and partners in society or the community can be the result of effective leadership (Riso et al., 2017). These systems can facilitate the advancement of various health-related initiatives and the real-time visualisation of health data. According to Meeks, Takian and Sittig (2018), the three most frequently claimed reasons for integrating activities are to improve patient care, reduce pointless visits, and prevent pointless hospitalisation.

2.7.6 Inadequate ICT skills in public healthcare institutions

Basic computer skills are needed for entering patient health data into the system. It can be difficult to appropriately enter patients' medical information since some medical personnel lack these skills (O'Donnell, Kaner, Shaw & Haighton, 2018). Healthcare personnel have been unable to use any type of technology due to a lack of computer literacy and assistance. Low computer navigational skills have restricted the usage of computers in developing nations (Owolabi, Evans & Mhlongo, 2016). More than any other technology feature, the human participation characteristic significantly slows adoption. Clinical doctors in South Africa reported average and below-average computer skills (42% and 45%, respectively). Only 12% of physicians in practice reported having computer abilities (Owolabi et al., 2016). In contrast, Awol (2020) discovered that there was a dearth of EHR knowledge and poor computer capabilities in a cross-sectional examination of four basic hospitals in Ethiopia.

To improve the quality of medical data that is available to them, medical professionals must also learn the computer skills necessary to access patient information. Therefore, instruction in using computers and obtaining patient data relevant to clinical practice will be given to healthcare professionals (Owolabi et al., 2016). Interdisciplinary healthcare employees say that their fundamental computer abilities are fair to good (Kujala, Hörhammer, Kaipio & Heponiemi, 2018). There may be more clarity regarding the professional's obligation to promote patient use of e-health services. The competence of healthcare professionals to communicate with patients using eHealth technologies and to counsel and encourage patients to adopt eHealth services were both given low ratings (Haigh, 2018).

2.8 SUMMARY OF THE CHAPTER

An overview of the world's healthcare systems and a discussion of the problems caused by the ageing population and the increase in chronic diseases were included in this chapter's beginning. A review of the available literature was presented in the section that followed, outlining some of the shortcomings of traditional paper-based records in the delivery of healthcare that electronic health records can address. The adoption of e-Health IS in developed and developing countries was also discussed at in the context of socioeconomic, political, and technical constraints. In addition, the literature reviewed argues that while some problems are shared by rich and developing countries alike, the ways in which EHR systems are implemented in each one differs depending on organisational, technological, and environmental factors.

These constraints include poverty, a lack of funding, a lack of human resources (healthcare professionals), problems with the infrastructure, a lack of system integration, and inadequate planning. In addition, the goal of the literature evaluation for this chapter was to investigate the benefits and drawbacks of utilising EHR systems in the setting of secondary healthcare. There are healthcare systems, but they cannot achieve the same results as the South African health system if they operate independently. For these technologies to work together and build a more effective healthcare system, interoperability is required. Chapter 3 of the thesis will discuss the development of the conceptual framework, which was validated and tested in Chapter 5.

CHAPTER 3: CONCEPTUAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

3.1 INTRODUCTION

The previous chapter discussed information system implementation in healthcare and hospitals, including eHealth system principles and definitions as well as the benefits of eHealth adoption. This thesis uses the existing literature to develop a conceptual model and hypothesise relationships between the key constructs in this chapter. In the next chapters, the model will be empirically tested. A review of prior studies on the organisational, environmental, and technological challenges that eHealth systems face is included in this chapter. In addition, the main objective of this chapter was to outline how a conceptual model for the study was developed.

This chapter further focuses on the development of hypothesised relationships as illustrated in Figure 3.2, based on the literature mentioned in the previous chapter. Relationships between the following research constructs: information quality (IQ), service quality (SQ), knowledge quality (KQ), electronic health records (EHR), medical error reduction (MER), perceived usefulness (PU), perceived ease-of-use (PEOU), technical context (TC), organisation context (OC), environment context (EC), dependent variable evidence-based healthcare practise (EBHP), and mediating variables: diagnosis and treatment of diseases (DTD) as well as better coordination of patient care (BCP). Each relationship's relevance is supported by data from past academic studies. The chapter ends with a summary of the relationships that have been proposed based on the developed conceptual framework.

3.2 THEORETICAL FOUNDATIONS

Many theories and models have been developed to guide and clarify the implementation of eHealth (Kitson, 2018). Despite this richness, research from several evaluations indicate that just a few carefully chosen theories have been applied regularly across numerous publications and by a variety of writers (Davis, Campbell, Hildon, Hobbs & Michie, 2015). For instance, the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) both accounted for 20 instances of theory used in a recent assessment of 24 studies on end-user acceptability of telemedicine by Harst, Lantzsch and Scheibe (2019). Different technology adoption models have been applied to comprehend how people accept a technology (Oye, A'Iahad, & Ab'Rahim, 2014). Understanding customer attitudes toward IT is a crucial area of study for information systems (Venkatesh, Davis & Morris, 2007). For a better understanding of how people perceive, accept, and use technology, models of technology adoption have been developed (Venkatesh, Morris, Davis & Davis, 2003). The subject has been studied in the field of computer science since the 1970s, when software engineering researchers began examining the adoption, acceptance and use of information systems (Momani & Jamous, 2017).

For the adoption of EBHP, this thesis proposes a hybrid strategy. The technological acceptance model (TAM), (Davis, 1989) the technology-organisation-environment framework (TOE), DeLone and McLean, (1992), and DeLone and McLean, 2003 are all used to build the hybrid model. The TAM was selected for this study because it concentrates on how specific users perceive technology and evaluates how those perceptions may influence their behaviour intention. To attempt to connect the characteristics of technology with those of the internal and external environments of the organisation, previous research employed the TOE framework (Chau et al., 2020; Chatterjee, Sheshadri, Nripendra, Rana, Yogesh, Dwivedi, Abdullah & Baabdullah, 2021) to help explain how new technology is used. On the basis of the literature reviewed, TOE was deemed appropriate for this study and D&M IS Success Model served as the main underpinning theory for this investigation.

a). DeLone & McLean model for information system success

In 1992, DeLone and McLean established the DeLone and McLean Information System (D&M IS) Success Model. An information system's model is made up of named variables that represent the system's quality, the information's quality, how it is used, how satisfied users are with it, how it affects individuals, and how it affects organisations. As a theoretical basis for IS success measurement, the model has received widespread acceptance and citations (Al-Okaily, Rahman, Al-Okaily, Ismail, & Ali, 2020; Gharaibeh &

Gharaibeh, 2020; Al-Hattami, 2021). The DeLone and McLean idea was initially harshly criticised, despite its early success. For instance, a number of studies (Ballantine, Bonner, Levy, Martin, Munro, & Powell, 1996; Hu, 2003; Seddon & Kiew, 1994) have demonstrated that the DeLone and McLean model was inadequate in addressing the needs of evaluating the success of IS projects in various scenarios and accounting for key elements of IS project performance. DeLone and McLean revised their model in response to the criticism and created a new version that incorporated extensive assessments of the model made by the research community over the ten years following its initial publication (DeLone & McLean, 2003). With the assistance of academics, an updated version of the IS success model was created (Seddon, DeLone, & McLean, 2003). The improved D&M IS Success Model is depicted in Figure 3.1.

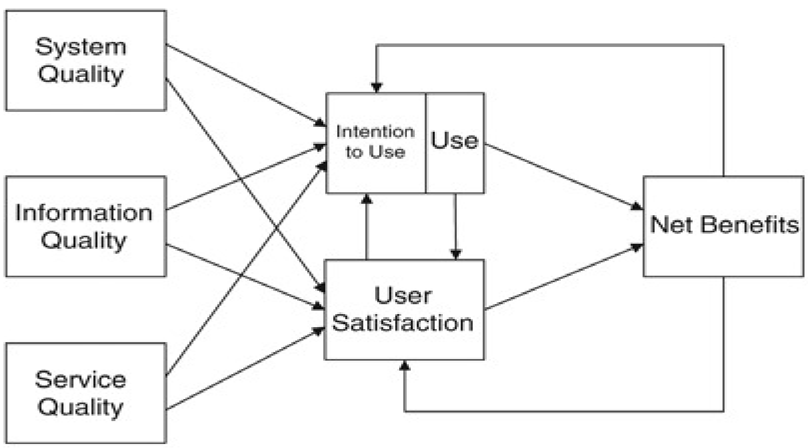


Figure 3.1: The updated D&M IS Success Model

Source: (DeLone & McLean, 2003)

For investigating the critical success factors for the adoption of evidence-based healthcare practice at DGMAH this study used the updated D&M IS Success Model as the main underpinning theory. Since then, a number of IS studies have used this model to assess the effectiveness of health information systems (HIS) (Ojo, 2017). There are several ways to assess the effectiveness of an information system, as was already mentioned (Ojo, 2017). D&M IS Success Model developed by Delone and McLean assesses the system's performance from a broad perspective by identifying, assessing, and elucidating the relationships among six success dimensions: system quality, information quality, service quality, use, user satisfaction, and net impacts (Delone & McLean, 2016).

According to Delone and McLean (2016), "net benefits" one of the six dimensions that measures system outcomes from both a positive and a negative angle. Net benefits impacts are strongly influenced by all other dimensions and the study's setting (Delone & McLean, 2016). Negative results may result in decreased usage and user satisfaction. On the other hand, successful outcomes may increase utilisation and user satisfaction. (McLean & Delone, 2016). Although using the system offers more advantageous results, there is a reason for doing so (Delone & McLean, 2016). Businesses can collect feedback from a growing number of customers on the system, information, and service quality in order to pinpoint potential faults and improve their product (Delone & McLean, 2016).

Kilsdonk et al. (2017) evaluated the success and the comprehension of the aspects of how the HIS "fits" into the organisation using the DeLone and McLean Success Model in conjunction with the human, organisation, and technology-fit (HOT-fit) framework. The 'fit' of an HIS is required as a strategy's final goal in order to comprehend execution on an eHealth system. According to Kilsdonk et al. (2017), concentrating on and fostering positive belief variables as well as dispelling unfavourable ones early on with participation might improve acceptance of systems like clinical decision support systems as a component of a comprehensive HIS. Due to the complexity of HIS, it is essential that information systems are properly matched, logical design principles are followed to ensure accurate information exchange, and all systems function consistently to support the daily needs of medical professionals.

In numerous health information systems studies, both developed and developing countries have tested and used the D&M IS Success Model. Jensen, and Udsen (2016) stated in their study that the D&M Model offers a practical framework for assessing health information systems. For instance, when analysing the antecedents of Electronic Medical Record (EMR) system deployment success in Ethiopian hospitals, it was found that the constructs of D&M Model were useful in predicting the efficiency of a system (Tilahun & Fritz, 2015). In another study conducted by Cho, Bae, Ryu, Kim, An, and Chae (2015), the effectiveness of recently installed information systems at three public hospitals in Korea was also examined using the D&M IS Success Model. Their research revealed that the quality characteristics had strong correlations with user satisfaction and net benefits, which supported the hypothesis (Cho et al., 2015). Information, system, and service quality are some of these characteristics of quality. The adoption of the updated D&M IS Success Model's objective in the current study was to determine the impact of newly introduced and modified constructs, such as knowledge quality (KQ), electronic health records (EHR), medical error reduction (MER), diagnosis and treatment of diseases (DTD), better patient care coordination (BCP), on the adoption of evidence-based healthcare practise (EBHP) at DGMDH. This is covered in greater depth in Section 3.3.1.

b). Technology acceptance model

The most popular approach for determining the factors affecting technology acceptability was developed by Davis in 1989 and is known as the technology acceptance model (TAM). To better understand how users, act and intend to utilise technology, academics as well as researchers employ the theory of reasoned action (TRA), which serves as the foundation for TAM (Marangunic & Granic, 2015). Rondan-Catalua, Arenas-Gaitán, and Ramrez-Correa (2015) claim that the goal of TAM is to be able to explain user behaviour across various end-user computing technologies and user groups and to identify the factors that influence broad computer adoption. In this study, TAM was used to examine the critical success factors that previous studies suggested might exist. Rho, Yoon, Kim, and Choi (2015) suggest that TAM may be useful for forecasting the adoption of innovations in the healthcare ecosystem. Researchers have used TAM to gain a better understanding of how doctors use telemedicine (Saigi-Rubió, Jiménez-Zarco, & Torrent-Sellens, 2016). According to Wade, Grey, and Carati (2016), the PEOU and PU constructs are related to users' aspirations to use telemedicine.

In their investigation, Pai and Huang (2016) acknowledge the importance of TAM in the IS literature. The theory of reasoned action (TRA), which was developed independently by Fishbein and Ajzen, is also the foundation of TAM. The theory of reasoned action (TRA) and the theory of planned behavior (TPB), which investigated the factors influencing behavioural intention, are the theoretical foundations for this idea (TPB). PEU and PU are two of the belief structures in the model. According to Davis, Bagozzi, and Warshaw (1989), "attitude toward use" and "behavioural intention to use" are two additional TAM dimensions that have an impact on a user's decision to adopt technology. In TAM, perceived technology usefulness and ease of use predict behavioural intention indirectly, whereas a person's attitude directly influences it. "Perceived usefulness" is the arbitrary possibility that utilising a specific application system will improve a potential user's job performance in an organisational setting (Davis et al., 1989). A technology's perceived usefulness (PU) measures how much a user's productivity will be improved (Wu & Chen,2017; Zhang et al.,2017).

TAM might be able to predict how quickly technologies will be adopted in the healthcare ecosystem (Rho et al., 2014). In addition, TAM has been used by researchers to better understand how physicians use telemedicine (Saigi-Rubió et al., 2016). According to Rho et al. (2014), the TAM model has become the industry norm for understanding and predicting the uptake of technology. Technology acceptance was defined by Rho et al. (2014) as the psychological state of users and how it affects how they intend to use technology. The most widely used conceptual model for predicting technology use intention and actual use is called TAM (Chen et al., 2017). Each of these frameworks also has benefits and drawbacks.

In some studies, two or more of these frameworks have been combined to enhance each other's capabilities (Oliveira, Thomas, & Espadanal, 2014; Yigitbasioglu, 2015). This conceptual model also incorporates the TOE framework, which integrates technology, organisation, and environment. In addition, TOE framework is useful as a governing framework in which a range of characteristics from other frameworks can be borrowed and combined since, unlike the technology adoption frameworks previously discussed, it has no fixed set of attributes and can adapt for different types of technology. Furthermore, the study's discussion of TOE's emphasis on technological, organisational, and environmental factors that influence technology adoption will be covered in more detail in the following section.

c). Technology-organisation-environment framework (TOE)

To predict the likelihood of IT adoption, the technology organisation environment (TOE) framework makes a standard set of assumptions (Ahmad, Bakar & Ahmad, 2015). According to the theory, adoption is influenced by business operations, organisational changes, and the environment of the industry (Awa et al., 2015). TOE theory asserts that new ideas are embraced and put into practise in three separate ways: technologically, environmentally, and organisationally (Borgman, Bahli, Heier, & Schewski, 2013). In addition, there are also benefits and drawbacks to adopting innovation in those situations (Borgman et al., 2013). According to Borman et al. (2013), the internal and external technologies that organisations utilise are referred to as the TOE framework's "technology context." The TOE framework's organisational context details an organisation's resources, size, and internal communication strategy (Borgman et al., 2013). Environmental context, as defined by AlKalbani, Deng, and Kam (2015), is the presence of external circumstances that compel enterprises to adopt specific technologies.

Furthermore, these three constructs frequently include a variety of factors that affect how businesses adopt new technologies (Alkalbani et al., 2015). The TOE Framework has been used in numerous technology adoption studies to examine a variety of technologies (Kamble, Gunasekaran, Subramanian, Ghadge, Belhadi & Venkatesh, 2021). This demonstrates that the TOE framework has acquired significant and reliable empirical support in a variety of fields, and that prior researchers found it useful when analysing organisational-level adoption. It should be noted that some of the most recent studies addressed contextual influences on the adoption of RFID in light of the TOE framework (Cao, Jones & Sheng, 2014). These studies Tsou and Hsu (2015) evaluated variables to account for the uptake of mobile hotel reservation systems and looked at relationships between the application of the TOE framework, the co-production of services, the accessibility of digital resources, and the performance of businesses (Zhang, Sun, Yang, & Wang, 2020).

In conclusion, TAM has greater flexibility in the external variables it chooses and is better equipped to capture the acceptance behaviours of the individuals, whereas TOE considers the technical, organisational, and environmental aspects that have an impact on technology acceptance and adoption at the organisational level. The advantages of

TAM and TOE may be combined, and the adoption behaviours at various levels could be captured. For instance, Gangwar et al. (2015) integrated the TAM and TOE models and used them to investigate the organisational level cloud adoption process. Therefore, TAM and TOE were both adopted in this investigation based on the literature review.

3.3 THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

A theoretical framework, according to Varpio, Paradis, Uijtdehaage and Young (2020) is a logically constructed and related collection of ideas and problems that are derived from one or more theories and serve as a researcher's guide for a study. A researcher must describe the ideas and theories that served as the study's framework while developing a theoretical framework. In addition, the researcher must draw connections between the theories, issues, and the current research. The updated Delone & McLean IS Success Model was also chosen as the study's primary theoretical framework since it is a multidimensional measuring model with links between different success characteristics and determines the success of IS and their related metrics (Delone & McLean, 2003). Based on the theoretical underpinnings of TAM: Davis (1989); Davis et al. (1989), TOE framework: Tornatzky and Fleisher's (1990), and the updated D&M IS Success Model, the researcher established an integrated conceptual framework for evidence-based healthcare practise. This prevents any issues that would have arisen if the study had been built around a single adoption framework.

Six constructs: system quality, information quality, service quality, (intention to) use, user satisfaction, and net benefits from the updated D&M IS Success Model were adopted and used in this study. These constructs were chosen to help identify the critical success factors for the adoption of evidence-based healthcare practices at a South African public hospital. Many studies continue to use the traditional frameworks in their current form, even though some studies combine them or add or remove variables (Taherdoost, 2018; Barrane, Karuranga & Poulin, 2018). Researchers such as Khalilzadeh, Ozturk and Bilgihan (2017) have proposed increasing the number of external variables which could enhance this model's capacity to forecast the adoption of IT. Trust and individual IT-specific innovation were added to the UTAUT model by Kabra et al. (2017) in order to analyse the factors that influence users' behavioural intentions to use IT. To help achieve the proposed goal of the current study, the three adoption models were combined to develop a framework for evidence-based healthcare practice that will be discussed in the following subsections.

3.3.1 Updated D&M IS Success Model Constructs

Even though the D&M IS Success Model been updated, several researchers noted that it needs further validation to be used as a theoretical basis for IS success evaluation (Roy & Balaji, 2015; Chang & Chen, 2016; Wang, 2014). However, some modifications have been made to suit the study specificities. The justifications for these modifications are provided as well. As depicted in Figure 3.1 all the six constructs: system quality, information quality, service quality, system utilisation, user satisfaction, and net benefits were adopted in the current study. This section will discuss each construct, how it applies to the study, and why it was selected.

i. System quality

According to Lau and Kuziemsky (2016), availability is the ability to access data and information continuously. This implies that the information or data is immediately available and usable by a designated person or organisation. Several factors are considered when evaluating the quality of a system, including its usefulness, technical adaptability, system accuracy, response time, and usability (Lau & Kuziemsky, 2016). EHR systems enable greater levels of information sharing and cross-organisational cooperation. The decrease in overprescribing is one advantage of EHR systems (Vos, Boonstra, Kooistra, Seelen & Van Offenbeek, 2020). In this study systems quality was changed to read electronic health records (EHR). Damen et al. (2022) state that the major duties of an EHR are to collect patient data, keep track of orders and results, support clinical decision-making, facilitate electronic communication, help patients, carry out administrative tasks, and report on population health.

EHR systems also encourage communication between patients and medical professionals (Misto, Padula, Dame, Molloy & Nimmagadda, 2020). Better patient outcomes and patient comprehension of their conditions and available treatments are frequently the results of these discussions. EHR will therefore provide integration of clinical documentation with physician orders, pharmaceutical dispensing systems, laboratory data, and other related systems to enable a high level of system quality in the context of this study. Numerous studies have found a connection between user satisfaction and information quality that is both direct and significant (Gürkut & Nat, 2017; Jaafreh, 2017; Ojo, 2017).

ii. Information quality

One of the most crucial tasks carried out by basic healthcare practitioners is diagnosis (WHO, 2016). The failure to explain the patient's medical issues accurately and promptly is referred to as a diagnostic mistake (Singh, 2014). These are widespread and present in all healthcare systems. According to some research Cea Soriano, Zong, and Garca Rodrguez (2019); Summers, O'Neill, Church, Collins, Sargan, and Brodbelt, (2019), EHR can enhance patient care standards and patient safety. For instance, EHR systems typically encourage improved communication among hospital medical staff members at all times and everywhere. EHR systems enable higher levels of communication and interorganisational cooperation among healthcare professionals. One benefit of EHR systems is the reduction in overprescribing (Vos, Boonstra, Kooistra, Seelen & Van Offenbeek, 2020).

In addition, information systems are essential to the practice of evidence-based medicine because they give healthcare professionals access to clinical evidence and data about their patients' health as they develop patient-care initiatives (Al Alawi, Al Dhaheri, Al Baloushi, Al Dhaheri & Prinsloo, 2014). Information output attributes including adequate detail, readability, and completeness provided by an HIS are all examples of information quality (DeLone & McLean, 2003). Health care professionals can improve their ability to create better diagnoses, treatment plans, and provisions for patient care by acquiring patient information (DeLone & McLean, 2003; Tilahun & Fritz, 2015). They might perceive HIT more highly if they acknowledge these clear advantages (DeLone & McLean, 2003). The reviewed literature highlights the importance of considering information quality (IQ) as a crucial construct in the adoption of evidence-based healthcare.

iii. Knowledge quality

Prior studies in developed countries have demonstrated that introducing a knowledge management system (KM) in hospitals can raise patient care standards, enhance treatment protocols, and increase knowledge sharing among medical professionals (Hassan & Der, 2014). The healthcare stakeholder community supports interoperability because they believe it has the potential to enhance patient care, lower costs, and lower medical errors. However, the transition from a standalone EHR system to an enterprise health information network has been stressful and upsetting (Anderson et al., 2017). EHR's primary goal is to facilitate the analysis, communication, and application of knowledge from EHR by integrating knowledge from patient health information in preventing medical errors. Explicit or documented forms, such as clinical procedure guides, clinical workflows, and electronic health records (EHR), are created from tacit knowledge (experiences or professional practices of caregivers) (Salleh, Zakaria & Abdullah, 2016).

Sharing health information between patients and providers may improve diagnoses, patient education, and promote self-care (Mohajan, 2016). In this context, knowledge quality (KQ) was selected as the study's new construct. The healthcare industry is transitioning to a knowledge-based society that places a significant emphasis on knowledge management in order to improve patient care. Futher, in today's information-based society, knowledge sharing or how to exchange knowledge to develop or deliver the best benefits for the organisation such as healthcare institutions is an essential knowledge management activity (Dessie, 2017; Lee, 2017). Knowledge sharing is one of the most crucial elements of knowledge management (Alhalhouli, Hassan & Der, 2014). According to Melnyk and Fineout-Overholt (2014), Evidence based practice (EBP) and in this study Evidence based healthcare practice (EBHP) incorporates a methodical search for and critical evaluation of the most pertinent clinically relevant evidence, individual clinical competence, and patient preferences and values.

iv. Service quality

Clinical and administrative tasks cause delays in patient discharges that extend hospital stays and may lower healthcare quality while also raising costs (Murti Deshpande & Srivastava, 2013). According to researchers (Chakraborty, Kaynak, Pagán Chakraborty, 2021), the quality of care is seen as a crucial part of the healthcare system. Lack of finance and resources present challenges for the healthcare system, yet the need for high-quality treatment remains constant (Health Systems Trust, 2019). South Africa is one of the few countries with clearly visible wealth inequality. According to Sikhondze and Erasmus (2016), South Africa's public healthcare institutions provide poor healthcare services the same as those found in other countries. In this study, service quality was also one of the constructs that was adopted from the updated (D&M) IS Success Model's construct and was used to develop this model. In service-related industries like healthcare, the perceived or expected quality is used to assess service quality. Christine (2019) and Tejaswimateri (2018) define service quality as "the patients' judgment or perception of a healthcare unit's overall excellence and superiority" by drawing on earlier research.

In addition, some studies have discovered a connection between customer satisfaction and the use of IS services (Jaafreh, 2017; Ojo, 2017; Mkala, 2018). DeLone & McLean (2016) also came to similar conclusions when they found a link between information systems and service quality. Therefore, providing quick and dependable support based on user-specific needs may improve the provision of goods or services to IS users. However, the lack of essential service quality attributes may undermine the system's ability to deliver effective service content, making user operations more difficult (Shagari & Abdullah, 2017). A meta-analysis of the information systems success model (ISSM) (Wang, 2016) found a positive significant relationship between user satisfaction and system quality, information quality, and service quality (SQ). No modifications were made to the construct of service quality; it was accepted based on the literature mentioned above.

v. Medical error reduction

According to Tabor and Ringsted (2017), medication errors are among the most prevalent reasons why patients experience unintentional injury. Pharmaceutical errors can also be fatal, and they have even caused patient fatalities in some cases (Jankovic et al., 2018). Preventable prescription errors affect more than 7 million individuals, costing the US healthcare system as a whole roughly $21 billion annually (Da Silva & Krishnamurthy, 2016). The total cost of prescription errors is far higher when lost wages, disabilities, lost productivity, and the cost of maintaining health are considered. This is a major issue that has to be resolved (Palabindala, Pamarthy & Jonnalagadda, 2016). As shown in Figure 3.2, MER has a direct impact on how diseases are diagnosed and treated, with EHR acting as a catalyst. The researcher chose to include "medical error reduction" (MER) as a new construct to the D&M IS Success Model in the current study based on the literature review.

This study assumes that the MER construct will be significant in the context of this research study. The justification is based on the fact that one of the key healthcare functional areas where electronic medical record systems are intended to provide solutions is the documentation and provision of patients' fundamental clinical and demographic information such as identification information, clinic attendance information, known allergies, test results, weight and height, among other things (Msiska et al., 2017; Waithera, Muhia & Songole, 2017). It provides clinical decision support by highlighting abnormal test results, warning healthcare professionals of abnormal vital signs, informing them if a prescription contains an allergen or if a recorded drug is used and prompting them to perform recommended tests, take prescribed medication or receive recommended care (Melanie, 2016).

vi. Better coordination of patient care

According to recent studies Graber, Byrne and Johnston (2017), Schopf, Nedreb, Hufthammer, Daphu and Laerum (2019) electronic health record (EHR) systems are an essential tool for enhancing the quality, efficacy, and safety of healthcare. In other words, utilising such technologies enhances patient monitoring, decision-making, and record-keeping, enabling medical professionals to provide better care. The mediating variable "intention to use" was adopted from the D&M IS Success Model. To better represent the objective of the current study, the construct was changed to read "better coordination of patient care" (BCP). When mediation occurs, a third variable that the mediator controls can (in part) explain how two variables are related (MacKinnon, 2017). In this study BCP serves as a mediating variable between electronic health records (EHR), knowledge quality (KQ), information quality (IQ), and evidence-based healthcare (EBHP), as shown in Figure 3.2.

Hasanain et al. (2017) claim that because medical records are succinct, precise, and contain information about a patient's medical history, which is the most reliable source in clinical diagnosis. Medical records include information about a patient's complaints, examination findings, and medical interventions in addition to serving as a written record of the patient's medical history (Vesna, 2014); they also include information about the results of diagnostic laboratory tests, physician opinions, medical procedures used, therapeutic methods, and medications (El-Gayar & Timsina, 2014). According to the aforementioned literature, the use of EHR will enhance patient care coordination and lead to more precise disease diagnosis and treatment. Professional nurses' knowledge of various patient procedures from admission through discharge gives sequential data, information, and records (Jane, 2016). Siu (2015) concurs that nursing knowledge includes specific information about patient problems and strategies for preventing those difficulties. According to Shaari, Bakri, and Rahman (2015), nurses make up the largest group of healthcare workers and carers in all healthcare settings and are essential to giving patients better treatment.

vii. Diagnosis and treatment of diseases

According to Salvage & White (2019), nurses make up the bulk of healthcare professionals worldwide and are crucial to providing healthcare. Knowledge management can aid practitioners in making wiser choices, which can lower the likelihood of medical errors and the associated costs (Mikk, Sleeper, & Topol, 2017). Knowledge management can lower drug prescription errors, with certain examples demonstrating reductions of up to 55% (Mulate & Gojeh, 2020; Zaher, 2016). A coordinated inter-professional care plan is particularly essential because, according to research (Mikk et al., 2017), a lack of teamwork in the medical field is a primary cause of many medical errors. In order to acquire and produce new information and subsequently improve the quality of treatment, it is crucial for healthcare professionals to share knowledge, collaborate among themselves and broaden their expertise. Improving the quality of care is one of the fundamental goals of all health research.

Inaccurate diagnoses, inadequate treatments, pharmaceutical errors, dangerous hospital practises, a shortage of trained medical professionals with adequate training, or a lack of information currently have a negative influence in every country (WHO, 2018). The current study broadens the D&M IS Success Model by including diagnosis and treatment of diseases as a new construct and as one of the factors influencing evidence-based healthcare practise (EBHP). In the D&M IS Success Model, "user satisfaction" was changed to "diagnosis and treatment of diseases" (DTD), which now functions as a mediating variable in the theoretical framework. As depicted in Fig. 3.2, DTD serves as a mediator between electronic health records (EHR) and evidence-based healthcare practises (EBHP). Doctors can also collect and evaluate a variety of data from the patient's symptoms, signs, laboratory results, and x-rays in order to diagnose a patient and decide on the best course of treatment.

A patient has the highest chance of receiving the appropriate therapy when a diagnosis is made promptly and precisely, claim Holmboe and Durning (2014). This is so that clinical judgements can be made based on an accurate evaluation of the patient's health. In the absence of extensive and regular observation, the physician must use caution because knowledge gained only from clinical experience and intuition may be unreliable. Although it is crucial to comprehend the pathophysiology of any illness, doing so alone does not allow for the prescription of treatment plans and may lead to inaccurate predictions about the results of diagnostic procedures and the efficacy of therapies.

viii. Evidence-based healthcare practice

In most health sciences, including medicine (Sackett et al., 2000), clinical psychology (Spring & Neville, 2014), social work (Drisko & Grady, 2019), nursing (Rycroft-Malone et al., 2016), and forensic psychology, evidence-based approaches have now established themselves as the standard method for treating patients (Gannon & Ward, 2014). In EBP, "patient clinical diagnosis is derived from the systematic collection of data through observation and experiment, and the formulation of questions and testing of hypotheses" are considered to be examples of evidence (Spring & Neville, 2014). The goal of the current study was to broaden the definition of evidence-based practice. This definition has been modified to read "evidence-based healthcare practice" to better reflect the study's aim to identify factors that could influence the adoption of EBHP at a South African public hospital. According to conventional wisdom, a strong commitment to health care is necessary to advance people's overall physical and mental health and well-being on a global scale (Health Systems, 2019).

Effective medical records management (MRM), according to studies conducted globally, improves healthcare services by promoting evidence-based policy, clinical service, decision-making, and hospital administration (Marutha & Ngoepe, 2017). This was mentioned by Koech et al. (2017), who also noted that good MRM is needed to support effectiveness and efficiency in hospital service delivery. Net benefits construct from the D&M IS Success Model was adopted in this study and changed to read EBHP. In the suggested study framework (see Figure 3.2), this construct is a dependent variable. In this study it was hypothesised that MER has a direct beneficial impact on EBHP. The hypothesis was tested to scientifically validate this claim, even though the literature supports the hypothesized relationship. When easily accessible and shared by healthcare professionals, patient medical records offer high-quality data that can be utilised to make decisions about disease diagnosis and treatment (Hannemann, Straková & Vaek, 2020). The TOE and TAM constructs, which served as the study's guiding theories, were included in the D&M IS Success Model, which was covered in the next section. Furthermore, the literature covered section also concentrated on explaining why these constructs were chosen for this study.

3.3.2 Organisational, technological, and environmental framework constructs

The TOE framework's consideration of technological, organisational, and environmental constructs may offer a distinctive viewpoint on the adoption of IT (Pan, Froese, Liu, Hu & Ye, 2022). Furthermore, TOE framework is more robust than more conventional models like TAM and UTAUT since it incorporates both human and non-human variables into a single framework (Awa et al., 2015). Numerous research papers have connected the firm's TOE dimensions and a more thorough breakdown of the factors influencing technology adoption (Abed, 2020). According to empirical research that have made use of the TOE framework, it is a sound theoretical framework for describing and comprehending intents to embrace an innovation (Abualrob & Kang, 2016). Contrary to the presumption that the TOE's constructs are only pertinent and applicable to large enterprises, Awa et al. (2016) claimed that the framework can be experimentally validated across all firm sizes. The TOE is an integrated framework that provides a thorough theoretical foundation for study, according to Gono et al. (2016).

In the context of this study, it is believed that these three constructs; (technological, organisational, and environmental) context are crucial in determining the critical success factors in the adoption of EBHP at DGMDH. Furthermore, the justification is based on the theoretically sound foundation of the TOE framework and its potential application in the adoption of information systems (IS), (Oliveira & Martins, 2011). Organisational, technological, and environmental contexts were the three constructs adopted from TOE and will be discussed separately in hypotheses H13, H14, and H15. Al-Aulamie (2013); Waehama, McGrath, Korthaus and Fong (2014) contend that these theories fall short of explaining why people choose to use technology. This issue highlights the significance of adding a new variable to TAM to increase its capacity for explanation (i.e., usability). Perceived usefulness and perceived ease of use TAM constructs were incorporated into the (D&M) IS Success Model, which will be discussed in more detail in the following section.

3.3.3 TAM: Perceived usefulness and perceived ease of use constructs

This study investigated the effects of perceived electronic health records (EHR) usability and usability using TAM as a reference. Explaining why people use technology and how various factors affect this behaviour is the fundamental goal of TAM. The development of TAM was based on the perception of information technology's perceived usefulness (PU) and perceived ease of use (PEU)] (He et al., 2018). The perception held by healthcare providers that acquiring a patient's medical history through an EHR is generally effortless was defined as perceived usefulness for the purposes of this study. Perceived benefits alter beliefs about or plans to utilise a particular technology, and they increase perceived usefulness overall (Matikiti, 2018). Numerous studies (Nikou & Economides, 2017; Joo, Park & Lim, 2018) have found a substantial relationship between behavioural intention to use and perceived usefulness. In this study, an extension of these definitions, this study defines PU and PEU as a favourable subjective belief held by users that the adoption of an EHR will enhance the adoption EBHP.

TAM constructs PU and PEU, which are thought to be the most pertinent to the study were adopted and used in this investigation. These two constructs are discussed as individual constructs in hypotheses H11 and H12. The purpose of this study was to determine the relationship between the model's independent variables: IQ, KQ, EHR, MER, SQ, KQ, PU, PEU, TC, OC, EC, moderating variables: BCP, DTD and the dependent variable: EBHP. It was anticipated that three types of relationships positive, negative, or none at all will be established in an effort to assess the relationship between the independent, mediating, and dependent variables. The conceptual framework is depicted in Figure 3.2:

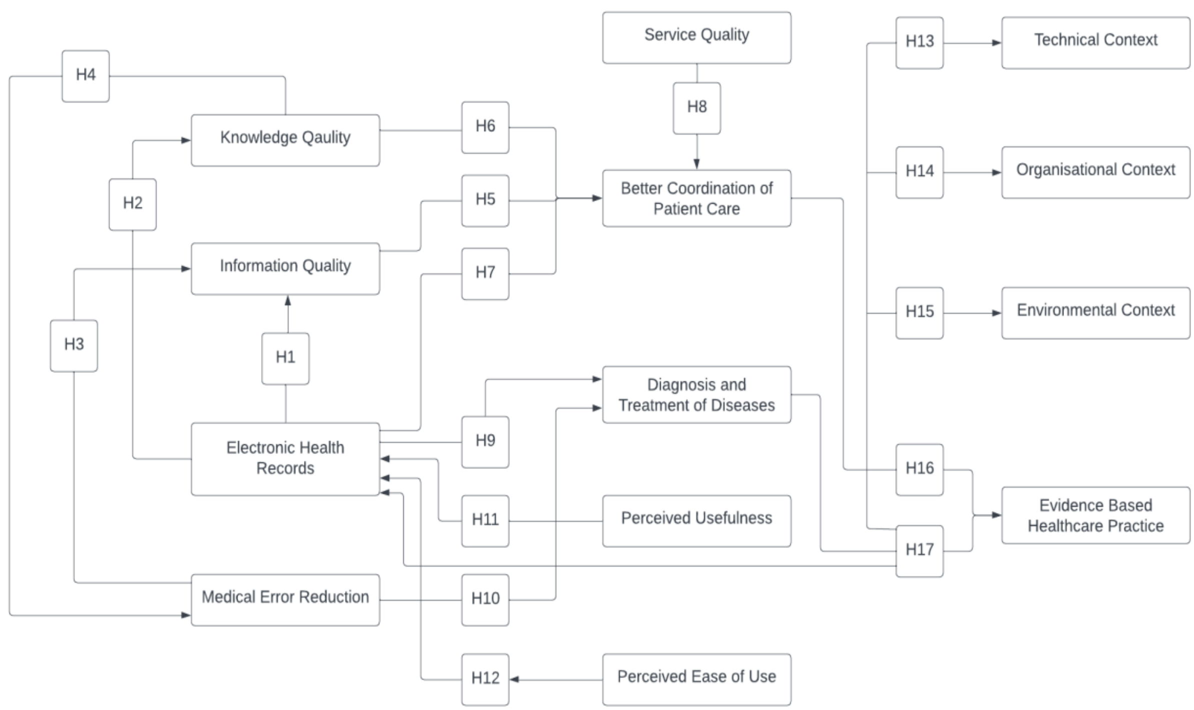


Figure 3.2: Conceptual framework

Source: Author’s own research

The next sections explore the significance of the model's variables after the research conceptual model has been introduced. Furthermore, earlier studies that gave comparable hypotheses were used to postulate and justify direct connections between the independent and dependent variables. This is indicative of a deductive strategy in which the researcher first develops ideas before putting them to the test (Bryman, 2016).

3.4 HYPOTHESES FORMULATION

According to Kumar (2019), one of a hypothesis' essential characteristics is that it must be related to an existing body of knowledge. In a technological acceptance study, hypotheses are required to regulate the interactions between model variables (Venkatesh & Davis, 2000; Sànchez & Hueros, 2010; Al-Harbi, 2011; Udo, Bagchi & Kirs, 2012). The combined hypotheses determine the direction of each interaction between variables, which controls the correlations in the resulting model. In addition, the study of research questions and/or hypotheses that describe phenomena, test relationships, evaluate differences, attempt to explain cause-and-effect relationships between variables, and assess the efficacy of interventions is included in quantitative research (LoBiondo-Wood & Haber, 2018).

The following sections will discuss the hypothesises based on the proposed framework in Figure 3.2.

3.4.1 Electronic health records, information quality and knowledge quality

Healthcare organisations can easily transmit information through EHR technology (Naidoo & Wills, 2016; Weaver et al., 2016). EHR technologies have also increased the ability to exchange and save digital information, making it possible to preserve all patient and history data on servers. Modern medical professionals assert that in order to enhance patient access and the management of health data, a change in the information-sharing paradigm and better interoperability are both necessary (Essén, Scandurra, Gerrits, Humphrey, Johansen, Kiergegaard & Ancker, 2018; Finset, 2018). Studies show that implementation of electronic health information system in healthcare institutions will speed up the process of digitisation, enabling the management of a variety of medical records, from patient information to prescription data and diagnostic treatment, in an easy, seamless, and straightforward way (Yoon et al., 2014).

A patient's medical history, lab results, and other pertinent data are instantly accessible to doctors who have access to the patient's health data through EHRs. However, it has also been noted that EHRs limit teamwork (Jiang, 2017; Chase, Ash, Cohen, Hall, Olson & Dor, 2017) as well as other aspects of medical practise (Colicchio, Cimino & Del Fiol, 2019). Doctors can update patient information in real-time to give other healthcare practitioners an accurate, up-to-date patient file (Hemsley et al., 2018; Krist, Beasley, Crosson, Kibbe, Klinkman, Lehmann & Waldren, 2014). Since continuity provides doctors with a solid foundation of the patient's medical history, it prevents clinicians from having to start over when a patient moves providers or visits a new doctor (Graber, Byrne & Johnston, 2017). From the literature reviewed, the following hypotheses were presented to investigate these relationships:

H1: There is a significant positive relationship electronic health records (EHR) and information quality (IQ).

H2: There is a significant positive relationship between electronic health records (EHR) and (KQ) knowledge quality.

3.4.2 Information quality, knowledge quality and medical error reduction

EHR systems support operational effectiveness and patient safety, specifically through enhancing patient care standards and reducing errors (Weaver, Ball, Kim & Kiel, 2016; Naidoo & Wills, 2016). The development of stronger structures and group cooperation are frequently encouraged by EHR. In addition, EHR systems encourage increased collaboration and communication between enterprises. Overall, operational performance across all enterprises has increased but the healthcare sector, as a whole, may have experienced an even bigger boost. Doctors and nurses collect and input clinical data about patients into an electronic health records system. According to Wang and Preininger (2019), managing and organising medical data is made simpler by an EHR system. Expanding patient access to electronic health records systems, according to researchers (Krist et al., 2014; Mikk et al., 2018), may improve health outcomes by empowering patients and encouraging better self-care.

Deokar and Sarnikar (2016) assert that lowering hospital costs can be achieved while also lowering medical errors, improving patient safety and increasing patient happiness. Healthcare firms can include more data sources in patient monitoring owing to EHR systems (Naidoo & Wills, 2016). Real-time data on prospective pandemics, for instance, might be helpful in assessing whether a patient has the flu and if so, which strain, when they are admitted to the hospital with flu-like symptoms (Naidoo & Wills, 2016). Real-time monitoring of more patients and broader medical trends are made possible by making information sharing between health institutions conceivable. Moreover, instantaneous access to a patients' medical histories, allergies and in some circumstances, the medical histories of family members ensures that patients are treated effectively and greatly enhances patient outcomes. Thus, patient outcomes are improved by EHR systems' enhanced capabilities (Naidoo & Wills, 2016). Based on the reviewed literature, the following hypotheses were proposed to investigate these relationships:

H3: There is a significant positive relationship between medical error reduction (MER) and information quality (IQ).

H4: There is a significant positive relationship between knowledge quality (KQ) and medical error reduction (MER).

3.4.3 Effects of information quality on better coordination of patient care

Healthcare providers must alter how they provide care, store records, and share them under the existing rules and norms in the health industry (Mantas, Housen & Hasman, 2014). EHR systems are now widely employed in the healthcare industry and follow all those rules and regulations. The development of EHR systems and the clear links between information technology improvements have led to this transition, which also involves the expansion of standards and laws controlling the record-keeping and data sharing of patient information (Campanella, Lovato & Marone, 2016). In addition, EHR systems promote interaction between patients and medical personnel (Misto, Padula, Dame, Molloy & Nimmagadda, 2020). These discussions frequently lead to better patient outcomes and patient understanding of their conditions and available treatments.

Implementation of EHR system enables practitioners to use evidence-based tools when deciding how to treat a patient. For instance, EHR systems allow for the identification of the situations in which a patient should seek additional care if a system evaluation shows that their health is deteriorating (Brom, Lukavsk, Greger, Hannemann, Straková & Vaek, 2020). Therefore, preventative care is crucial for lowering medical expenses and improving patient outcomes, particularly from the viewpoint of the community or population as a whole. EHR could also decrease billing errors (Atasoy, Greenwood, & McCullough, 2019). From the literature reviewed, the following hypothesis was proposed to investigate this relationship:

H5: There is a significant positive relationship between (IQ) and diagnosis and treatment of diseases (DTD).

3.4.4 Effects of knowledge quality on better coordination of patient care

According to Li, Pei, Chen, Song, Zhang, Yang, and Shaman (2020), electronic health record (EHR) systems are preferable to physical systems because they enable healthcare organisations to immediately identify and confirm when patients need care, check-ups, routine tests, and monitoring of their medical history. Due to this advantage, EHR systems might speed up a range of internal procedures inside a healthcare organisation, possibly even enabling quicker patient treatment with less concern for interactions or potential problems (Flieger, 2017). EHR systems enable quick searches and data extraction from patient records, saving healthcare professionals' time and energy from having to sift through files to find a patient's specific information in the past (Li et al., 2020). Similar to this, as soon as a patient receives care or an allergy is identified, their information is promptly updated and can be immediately shared with other departments or even other businesses (Li et al., 2020). In addition, since EHR system data is so widely used, it is possible to synchronise patient data between different institutions.

This promotes the standardisation of data in accordance with a set of standards, enabling access to the data by various EHR systems (Li et al., 2020). According to Li et al. (2020), this significant benefit of electronic records enhances all international healthcare systems. EHR systems also have the advantage of providing a strong case for regulation (Weaver, Ball, Kim & Kiel, 2016; Naidoo & Wills, 2016). In other words, implementing electronic systems increases the likelihood that regulations will be created. Information processing and coding can be standardized with the help of data from EHR systems. It has also been shown in the literature that, the regulation of health information storage, accessibility, and interchange may be significantly impacted by the standardisation of health care data in the context of a movement toward tougher regulatory requirements for health care data. In addition, the high level of security, and dependability of all medical records kept in EHR systems is guaranteed by data standardisation. The standardisation of EHR systems is another justification for healthcare institutions implementing such electronic record-keeping systems. Based on the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H6: There is a significant positive relationship between knowledge quality (KQ) and better coordination of patient care (BCP).

3.4.5 Effects of electronic health records and better coordination of patient care

Institutions of health care must prioritise preventative care as a top priority (Weaver, Ball, Kim, & Kiel, 2016; Naidoo & Wills, 2016). EHR systems have the capacity to enhance data analytics, identify fresh, data-driven treatment objectives, and develop plans to enhance patient outcomes (Doberne, Kakaday, Redd, Ericksson, Yackel, Marquard & Chiang, 2015). Similar to this, setting up an EHR system and integrating it with other healthcare systems can significantly improve a medical professional's capacity to establish treatment objectives that are favourable to successful patient outcomes. In addition, EHRs can assist the nurse in properly monitoring drug usage, which promotes improved drug utilisation and cost control. Also, provide support for medical information formats such as images and figures, mass archives, security, high dependability, standardisation of work procedures in hospitals, and facilitation of information sharing (Crowley, Mishra, Cruz-Cano, Gold, Kleinman & Agarwal, 2019).

These systems have been used to disseminate urgent clinical information and evidence-based care recommendations (Campanella, Lovato, Marone, Fallacara & Mancuso, 2016). Recently, electronic surveillance technology and decision support algorithms have been combined to create clinical alerts that have significantly improved inpatient sepsis management and decreased sepsis mortality (Manaktala & Claypool, 2017). Using information from EHR systems, researchers frequently pinpoint prevalent population-based healthcare trends and treatment effectiveness (Li et al., 2020). From the literature reviewed, the following hypothesis was proposed to investigate this relationship:

H7: There is a significant positive relationship between electronic health records (EHR) and better coordination of patient care (BCP).

3.4.6 Effects of service quality on better coordination of patient care

According to several studies, EHR can boost patient security and raise the bar for patient care (Al-Abri & Al-Balush, 2014; Naidoo & Wills, 2016). For instance, EHR systems frequently encourage improved hospital to hospital or clinic to hospital engagement. EHR systems enable greater degrees of information sharing and cross-organisational cooperation. Vos, Boonstra, Kooistra, Seelen and Van Offenbeek (2020) further argue that the decrease in overprescribing is one advantage of EHR systems. Electronic record systems have the undeniable advantage of significantly lowering waste in healthcare operations and patient care when compared to paper record system (Kocher, 2021).

Healthcare organisations emphasise patient education and awareness more because they promote self-control and medication adherence, which both improve patient outcomes (Misto, Padula, Dame, Molloy, & Nimmagadda, 2020). With the aid of summaries, reports, and the usage of EHR, nurses are now better able to make time to inform patients about treatments and any drug interactions. In addition, EHR systems have an increasing impact on patient education and awareness. They also foster interaction between medical personnel and patients (Misto et al., 2020). These discussions frequently lead to improved patient outcomes and patient understanding of their diseases and potential therapies. Based on the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H8: There is a significant positive relationship between service quality (SQ) and better coordination of patient care (BCP).

3.4.7 Effects of electronic health records on diagnosis and treatment of diseases

According to Khwima, Msiska, Kumitawa and Kumwenda (2017), EHR systems are intended to address a number of important clinical and demographic issues in healthcare including storing and transmitting information on identification, clinic attendance, known allergies, test results, weight and height—among others (Akor & John-Mensah, 2016). EHR systems can help to create new, data-driven therapy goals by enhancing data analytics and identifying ways to improve patient outcomes (Colombo *et al.,* 2020). Similarly, the implementation of an EHR system and its integration with other healthcare systems can considerably enhance medical practitioners' ability to identify treatment goals that are conducive to positive patient outcomes.

Further, EHR systems also decrease medication errors by facilitating effective doctor-patient communication and accurate information sharing. Patient information is shared between various healthcare departments. For example, doctors rely on the results of tests run by lab technicians to make diagnoses and prescribe the appropriate treatments. However, if a mistake is made when recording and sending the data, medical errors might not be preventable. Ineffective communication in the healthcare industry has detrimental effects, including incorrect prescriptions, delayed treatment, and incorrect surgical sites (Shitu, Hassan, Aung, Kamaruzaman & Musa, 2018). From the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H9: There is a significant positive relationship between electronic health records (EHR) and diagnosis and treatment of diseases (DTD).

3.4.8 Effects of medical error reduction on better coordination of patient care

According to researchers, giving healthcare providers more access to patient medical histories improves health outcomes by enabling people and promoting increased self-care (Hemsley, Rollo, Georgiou, Balandin & Hill, 2018; Mikk et al., 2017). The reasons and patterns behind healthcare institutions' failure to give patients adequate access to their outcomes must be found. EHR systems enable quick searches and data extraction from patient records, saving healthcare professionals' time and energy from having to sift through files to find a patient's specific information in the past (Colombo, Oderkirk & Slawomirski, 2020). For example, when an allergy is identified, patient information is promptly updated and can be immediately shared with other hospital departments (Colombo et al., 2020).

One of the clear benefits of EHR systems over physical systems is the ability of a healthcare organisation to quickly determine and confirm when patients are due for treatments, check-ups, routine testing, and the tracking of a patient's medical history Colombo et al., 2020). This benefit of EHR systems may lead to a number of internal processes within a healthcare organisation speeding up, maybe even enabling quicker patient treatment with less concern for interactions or potential problems (Campanella, 2015). Based on the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H10: There is a significant positive relationship between medical error reduction (MER) and diagnosis and treatment of diseases (DTD).

3.4.9 **Perceived** usefulness and perceived ease-of-use

a). Perceived usefulness

According to Alharbi and Drew (2016), perceived usefulness refers to how much users could expect new technology to improve their capacity to perform their job tasks. Artificial intelligence can be utilised in the healthcare sector to improve physician performance (Alloghani, Hussain, Al-Jumeily & Abuelma'atti, 2015). Medical healthcare professionals, on the other hand, will only endorse or implement artificial intelligence projects if they believe those would enhance their performance. In addition, a prior study in the healthcare sector discovered a link between perspectives on artificial intelligence (AI) project acceptance and benefits perception (Emad, El-Bakry & Asem, 2016).

The association between PU and someone's intention to use information technology is supported by a prior study (Tallaha, Shukor & Abu Hassan, 2014). According to Nysveen *et al.* (2015), the use of technology that does not aid its end users in performing their activities more successfully is likely not to be viewed favourably. Yeow, Soh and Hansen (2018) assert that when individuals are convinced of using a certain technology and potential benefits, they are more likely to use it. Perceived usefulness is the best indicator of technology adoption, and it significantly affects both the actual use of new systems and behavioural intentions, according to research on technology acceptance (Maranguni & Grani, 2015). From the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H11: There is a significant positive relationship between perceived usefulness (PU) and the adoption of electronic health records (EHR) at a South African public hospital.

b). Perceived ease of use

Venkatesh, Thong, and Xu (2016) observed that when people use technology, their perception of ease of use (PEU) or anticipation of ease of use is the assumption that it will be simple and painless. Similarly, addition, users will always evaluate the proposed information system's usability sooner after using it, considering their opinions of the information system products or services they are utilising at that time (Venkatesh et al., 2016). The perceived ease of use of any given system is defined as the quantity of technology used in conjunction with the perception of proper use of the specified technology. It has been investigated if artificial intelligence can be used in the healthcare industry (Alloghani, Hussain, Al-Jumeily, & Abuelma'atti, 2015).

PEU stands for the idea that if a technology is easier to use than a rival technology, it will be adopted more frequently by users (Moslehpour et al., 2018). For instance, it has been found that physicians value their autonomy in choosing the best course of treatment for their patients, so they are less likely to adopt an EHR system (Bahadori, Alimohammadzadeh, Abdolkarimi & Ravangard, 2017). These factors are also linked; for example, it has been shown that perceived usability is strongly correlated with management support and physician involvement, while perceived usefulness is strongly influenced by physician autonomy and the doctor-patient relationship (Bahadori *et al.,* 2017). Users are more likely to utilise a technical application if they believe it is simpler (Moslehpour et al., 2018). Based on the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H12: There is a significant positive relationship between perceived ease of use (PEU) and the adoption of electronic health records (EHR) at a South African public hospital.

The next section will discuss the impact of technological, environmental, and organisational constructs on the adoption of EHR systems as well as how the diagnosis and treatment of diseases influence on the adoption of evidence-based health practice.

3.4.10 Technological, environmental, and organisational contexts

a). Technological context

Technological aspects evaluate a range of parameters in terms of competitive advantage, interoperability, security issues and resource availability including resource accessibility and IT infrastructure. However, the implementation of EHRs in African countries has not been successful (Katurura & Cilliers, 2018). For instance, Malawi and Ghana have both attempted to establish a national EHR system, but issues such as a lack of government support and necessary infrastructure, an inconsistent supply of electricity and resistance from healthcare professionals have caused these initiatives to fail (Namakula & Kituyi, 2014).

Problems in this regard also include the lack of electronic data and power backups, inadequate IT infrastructure, lack of full-time IT specialists, lack of funding (Jawhari, Ludwick, Keenan, Zakus & Hayward, 2016; Gyamf, Mensah Kof & Oduro, 2017). In addition, the majority of the obstacles were created by people, among these were the adverse attitudes, actions, and convictions that healthcare professionals had regarding such systems (Tetteh, 2016). Several sources claim that a lack of funding, technological know-how and physicians' time constraints have all prevented the adoption of EHR (Raut, Yarbrough, Singh, Gauchan, Citrin, Verma, et al., 2018). From the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H13: The adoption of electronic health records (EHR) is influenced positively by IT infrastructure and resource accessibility.

b). Organisational context

The two organisational context constructs thus top management support and organisational readiness will be discussed in this section. According to this study, senior management support is one element that affects whether electronic health record (EHR) systems are implemented by public health institutions. Organisational support refers to the extent to which managers embrace a new technology system's technological potential (Jahanshahi & Brem, 2017). According to Laukka, Huhtakangas, Heponiemi, and Kanste (2020), organisational readiness for change is a well-known element that affects the success of organisational changes in general and the adoption of EHR in particular. EHR adoption is impacted by the organisational context, which strongly emphasises management support for system adoption capability (Mtebe, International & Alliance, 2018).

Similarly, top management in healthcare institution must adopt specific behaviours to assist the adoption of health information technology, according to a scoping assessment by Laukka et al. (2020). Leaders must behave as supporters, change managers, advocates, project managers, decision-makers, facilitators, and champions. According to literature, leaders also require a variety of informatics competencies, including computer and informatics knowledge, skills, and abilities (Strudwick, Booth, Bjarnadottir, Rossetti, Friesen, Sequeira, Munnery & Srivastava, 2019). However, as their comprehension of digitalisation and its implementation may not be much better than that of their subordinates, leaders are unable to properly perform their expected roles (Laukka et al., 2020). Based on the above reviewed literature, the following hypothesis was proposed to investigate this relationship:

H14: The adoption of electronic health records (EHR) is influenced positively by top management support.

c). Environmental context

Environmental factors may interact with an organisation when it crosses internal borders (Bolonne & Wijewardene, 2020; Xu, Ou & Fan, 2017). Competition pressure, according to Chen et al. (2015) and Park & Kim (2019), is the degree to which rival businesses embrace a certain IT innovation. The company may experience pressure as more and more rivals adopt the IT innovation and realise that it must implement it in order to remain relevant and competitive in its industry (Lautenbach et al., 2017; Sun et al., 2019; Verma et al., 2017). This study will examine vendor support as a component of the environment context. Vendor assistance relates to the vendor's capacity to provide technical support and training for the organisation's use of the cloud EHR system.

Fragidis and Chatzoglou, (2018) argue that the strategy approaches utilised in the adoption and implementation of EHRs might be top-down, centralised systems run by the government, or middle-out approaches where healthcare providers and IT suppliers gradually upgrade information systems to comply with the national information standards. It has been asserted that the United States of America (USA) supported widespread EHR adoption by using a bottom-up strategy (Fragidis & Chatzoglou, 2018). Feedback from users, the expertise of all key stakeholders, including nurses and doctors, and the fruitful collaboration of software developers, legislators, and administrators all play a significant role in the adoption of EHR systems (Ballaro & Washington, 2016). Ford, Silvera, Kazley, Diana and Huerta, (2016) further highlighted that, the effectiveness of the implementation process is also influenced by how organisational strategies and decision-making procedures are included into the vendor selection strategy. Contrary to popular belief, the goals of the vendor and the healthcare organisation are closely related (Olayiwola, Anderson, Jepeal, Aseltine, Pickett, Yan & Zlateva, 2016). From the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H15: Electronic health records (EHR) is influenced positively by vendor support.

Patient information was first digitised using electronic medical records (McMullen et al., 2014). They are a group of personal health records that are digitally recorded and kept by a physician during a patient visit (Ohuabunwa et al., 2015). Healthcare organisations that are able to properly adopt EHR systems stand to gain a number of advantages, including simple information access, enhanced patient monitoring and decision assistance, efficiency gains, and financial gains (Katsande, 2014). Additional benefits of implementing EHRs include improvements in patient care and safety (Heart, Ben-Assuli, & Shabtai, 2017). Patients' follow-up is aided by high HIT capacity, increased use of reminders, discharge summaries, and customised appointment scheduling (Hemsley et al., 2018).

HIT is crucial for enhancing patient outcomes, lowering medical errors and drug side effects, increasing productivity and protocol adherence, and lowering health care costs (Campanella, Lovato, Marone, Fallacara, Mancuso, Ricciardi & Specchia, 2015). According to van der Vaart, Drossaert, Taal, Drossaers-Baker, Vonkeman & Van de Laar (2014), patient web portals with EHR access give patients access to useful and understandable personal information. Utilising clinical, patient scheduling, and HR systems improves process quality, decision-making abilities, and encourages adherence to recommendations for best practices that are supported by research (Bardhan & Thouin, 2017). Based on the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H16: There is a significant positive relationship better coordination of patient care (BCP) and evidence-based healthcare practice (EBHP).

3.4.11 Effects of disease diagnosis and treatment on evidence-based healthcare

Evidence-based practice (EBP), evidence-based medicine (EBM), and evidence-based nursing practise (EBNP) are all choices considered while providing medical care or making medical decisions (LoBiondo-Wood, Faan, Haber & Faan, 2021). According to Camargo, Iwamoto, and Galvo (2018), EBP represents a substantial and fundamental paradigm shift for the entire planet. EBP is typically developed by identifying the problem, looking for solutions, weighing the options, and ultimately developing the evidence based on the experimental research that is currently available (Kristensen, Nymann, & Konradsen, 2015; Mitchell, 2016). This process aims to improve the quality of healthcare and patient outcomes. All healthcare specialities, including nursing, medicine, physical therapy, and other fields, regularly use the term "evidence-based practise" (EBP) (Florczak, 2017). EBP was used by multidisciplinary healthcare teams to enhance patient outcomes (Mitchell, 2016). To make well-informed, ideal healthcare decisions, EBM demands the clinician to draw on their clinical experience and knowledge, the strongest available research data, and patient preferences for treatment and care (Sackett, Rosenberg & Grey, 2018).

The term "evidence-based practise" (EBP), "evidence-based healthcare," and "evidence-based surgery" have all evolved, and this practise has been expanded to include other healthcare professions. Together, the patient and the physician make healthcare decisions using shared decision-making (SDM), which is supported by medical evidence, clinical knowledge, and patient preference and circumstance (Légaré & Witteman, 2016). Ideal patient preferences for care and treatment as well as their unique circumstances should be taken into consideration as doctors and patients debate the possibilities, advantages, and disadvantages of various healthcare solutions. In doing so, SDM has the potential to assist in the use of EBM during the decision-making process (Thériault, Bell, & Grad, 2019). According to Postema, Peeters, and Friele (2018), the electronic health information system has a great deal of potential to enhance organisational effectiveness, patient happiness, and safety. The treatment of the sick and injured who visit the hospital for treatment may suffer if the highly specialised knowledge in the hospital is not shared (Tang, 2017; Adewole & Opele, 2019). To effectively communicate and manage its tacit knowledge, the hospital's administration must make sure that it is clearly expressed (Haqani & Ahlan, 2015; Halawi et al., 2017). From the reviewed literature, the following hypothesis was proposed to investigate this relationship:

H17: There is a significant positive relationship between diagnosis and treatment of diseases (DTD) and evidence-based healthcare practice (EBHP).

The conceptual framework, which provides the justification for the variables' correlations and interactions, was developed after a synthesis of Information Systems (IS) theories and literature used to describe the phenomena. It acts as the guide for this study. Figure 3.2 provides a visual depiction of how the independent and dependent variables interact. The boxes represent the constructs which were measured by a set of items, with arrows representing Hypotheses H1 to H17.

3.5 CHAPTER SUMMARY

Based on the literature reviewed, this chapter attempted to develop a conceptual framework and a set of research hypotheses were formulated. Furthermore, an integrated theoretical model was developed, based on the updated D&M IS Success Model as well as TEO and TAM. Seventeen hypotheses were proposed, based on the conceptual framework. H1, H2, H3 and H4 assert that the use of EHR will lower medical errors and improve the quality of patient medical history information, leading to more precise patient diagnosis and treatment. According to the conceptual framework shown in Figure 3.2, the constructs of IQ, EHR, KQ, and SQ will all have a positive impact on BCP.

It was hypothesised that, EHR and MER, according to H9 and H10, will have an influence on DTD. H11 and H12 were based on TAM's two constructs: PEU and PU. Similarly, it was predicated that; these constructs will influence the adoption of electronic health records. TC, OC, and EC constructs addressed in H13, H14 and H15 were also hypothesised to have a positive significant influence on the adoption of EHR. Based on the proposed conceptual model it was predicted that, BCP, according to H16, will have a positive impact on EBHP, whereas DTD, H17 was predicated to have a positive impact on evidence-based healthcare practice as hypothesised in the conceptual model. The next chapter discussed the methodology employed in this study.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 INTRODUCTION

The previous chapter of this study provided a description of the theoretical underpinnings, the development of the research model and the formulation of the hypotheses for the current study. Furthermore, the purpose of the study was to understand how medical healthcare professionals see the clinical benefits of using electronic health records (EHR) and the perceived value of EHR data in assisting in clinical decision-making in the diagnosis and treatment of patients. In addition, theories adopted as well as constructs which were selected from each theory to develop the conceptual in Figure 3.2 and the hypotheses were discussed.

The main goal of this chapter was to propose a research methodology that will ensure that the research problem is addressed and that it is appropriate for achieving the research aims as well as in testing the hypotheses. For this reason, the first section of this chapter covers various research philosophies, techniques, and strategies before selecting and justifying the most relevant ones for this study. The chapter then covers a review and discussion of the many research methods available and the selection of the most suitable method for this study. This is followed by outlining the formulation and data collection method for the questionnaires. Finally, the pilot study and the ethical considerations are presented.

4.2 PHILOSOPHICAL FOUNDATIONS

Several presumptions will affect every step of knowledge development when conducting a research study. The researchers' values are represented by their research philosophy, which manifests in their publications (Saunders, Thornhill & Lewis, 2016). To establish an appropriate approach to a research topic and to provide important recommendations on how to address the research challenge in light of different worldviews, the philosophical foundations (paradigms) of research are essential (Shannon-Baker, 2016). Furthermore, the research philosophy determines the nature of the inquiry and its methodology. It reflects our perspective on the growth of knowledge (Pallant, 2014). As a result, a paradigm, or interpretive framework, is created, which shapes the research questions to be examined, the research methods to be employed, and the interpretation of the findings (Creswell et al., 2017; Brannen, 2017).

4.2.1 Research paradigms

A research paradigm has a significant impact on research methodology, according to Kivunja and Kuyini (2017). The methodological ramifications of the researcher's paradigmatic choice affect their research questions, the respondents they choose, the tools and procedures they use to collect data, as well as the data analysis. Four basic paradigms are beneficial in research and help researchers to choose relevant research issues and techniques to address them. Khaldi (2017) defines this approach as gathering, analysing, and using data on a phenomenon is referred to as a research philosophy. There are different subfields of research philosophy that can be applied to a number of areas, claim Daniel and Harland (2017). The four most common research philosophies in social scientific research are positivism, critical realism, and constructionism, according to Du Plooy-Cilliers et al. (2016). According to Du Plooy-Cilliers et al. (2016), each research paradigm has a precise ontology (where assumptions about reality are made), epistemology (which speaks to how knowledge is generated/created and what reality can be established from it), and axiology (which speaks to how values impacts/influence the interpretation of reality).

a). Pragmatism:

The pragmatic research philosophy places an emphasis on practical and applied research, according to Sekaran and Bougie (2016). This mentality embraces many viewpoints on a subject and often favours mixed methods research (Daniel & Harland, 2017). Various points of view, ideas, and theories can aid us in understanding any subject or phenomenon, in accordance with pragmatic theory (Kankam, 2019). The pragmatic approach also emphasises the connection between theory and practise (Sekaran & Bougie, 2016). According to Kankam (2019), pragmatist researchers are free to choose the approaches, methods, and processes they feel best suit the purposes and aims of the current research.

b). Positivism:

The belief that the truth can only be discovered via meticulous scientific examination serves as the cornerstone of positivist research (Sekaran & Bougie, 2016). A researcher must set aside all his or her personal feelings, ideas, and values to be an objective analyst, according to positivism (Davies & Fisher, 2018). Positivism makes it easier to provide accurate information free from ambiguity and/or biases (Kankam, 2019). According to Sekaran and Bougie (2016), positive theory asserts that the "goal of the research is to only describe phenomenon that one can directly observe and objectively measure." It should be noted that this worldview only has a relationship with quantitative research (Kankam, 2019).

c). Critical realism:

Critical realism, according to Sekaran and Bougies (2016), is the ability to have a particular understanding of the reality. Critical realism holds that the objective of research is to get as close as feasible to a desired result, even if it is impossible to actually achieve that result (Sekaran & Bougies, 2016). The presumptions required for a fuller understanding of people's subjective nature form the basis of the critical realism research philosophy (Zukauskas et al., 2018). When conducting research, critical realism takes this into consideration by considering phenomena like emotions, feelings, and attitudes (Kunaifi, 2021). Due to its incorporation of observations such as satisfaction, motivation, and culture and ability to facilitate the synthesis of viewpoints in order to advance towards an objective reality, this philosophy is thus relevant to both qualitative and quantitative research (Zukauskas et al., 2018).

d). Constructionism:

The constructionist research perspective aims to comprehend the principles that individuals use to interpret the world by looking at what goes on in people's brains (Sekaran & Bougies, 2016). This philosophy differs from those previously addressed in that it does not aim to find objective truth (Kankam, 2019). Contrarily, constructionism aims to produce knowledge (for humans) (Sekaran & Bougies, 2016). Despite being used in business and business studies research, constructionism, which is founded on cognitive psychology (Kankam, 2019), is less frequently used than other research ideologies. Learning more about how people see the world through their interactions with others and with the contexts in which those interactions take place is the major objective of the constructionist research perspective (Taylor, 2018). So, according to Kankam (2019), constructionism usually works best in conjunction with qualitative research.

In view of the available philosophical possibilities, positivism was selected for this study because, according to Sekaran and Bougies (2016), it best enables a researcher to concentrate on obtaining objective truth through observation and measurement. With a questionnaire that bans the researcher from influencing the respondents' responses. The main objective of the study was to identify the critical success criteria for the adoption of evidence-based healthcare practise (EBHP) at a South African public hospital. Based on the factors that were identified a framework for (EBHP) was then to be developed. Second, using structural equation modelling (SEM), seventeen formulated hypotheses were tested and validated in Chapter 5. Therefore, the researcher's values or prejudice had no bearing on the study's findings because the testing of the hypotheses was solely based on participant responses to questionnaires. This approach supports the positivist ideals as stated by (Antwi & Hamza, 2015).

4.2 RESEARCH DESIGN

Qualitative, quantitative, and mixed approaches are the three main research methodologies that are available. A single phenomenon is examined and thoroughly described when a qualitative research methodology is applied (Ravitch & Carl, 2019). The use of quantitative research, on the other hand, allows for the statistical analysis of the numerical data and the formulation of conclusions that are supported by the facts (Ravitch & Carl, 2019). A mixed technique of research is employed when the research has a dual objective, and a combination of quantitative and qualitative research methodologies is necessary (Babbie, 2017). According to Shikuku et al. (2018), the cross-sectional survey design is most suited for quantitative research since it allows for the examination of situations that occur in real life while focusing on a specific group of participants who meet the selection criteria. In addition, the cross-sectional survey approach facilitates the description and analysis of a wide sample of data while preserving the statistical significance of the findings (Shikuku et al., 2018). In a survey, participants' ideas and opinions can be elicited by asking the correct questions, according to Kelemba (2019), and the gathered data can then be utilised to do statistical analysis.

Furthermore, the cross-sectional survey design made it possible to pinpoint certain populations within a wide participant pool or even to focus on common traits, traits, and patterns that were evident in the extensive sample data (Kelemba, 2019). According to Shikuku et al. (2018), the data for the questionnaire-based survey is used as part of the quantitative investigations gathered with the least amount of effort while maintaining data quality. As previously stated, the main objective of this study was to identify the critical success elements for the adoption of EBHP at a public hospital in South Africa. From the identified critical success factors a framework for (EBHP) was to be developed. However, a questionnaire was developed based on the conceptual framework and the following constructs were included: information quality (IQ), electronic health records (EHR), knowledge quality (KQ), service quality (SQ),medical error reduction (MER), perceived usefulness (PU), perceived ease of use (PEU), technical context (TC), organisation context (OC), and environmental context (EC) and mediating: better coordination of patient care (BCP), diagnosis and treatment of diseases (DTD) to investigate these critical success factors and the participants in this study were medical healthcare professionals at Dr George Mukhari Academic Hospital (DGMAH).

Variables

These constructs mentioned above were adopted from the updated DeLone and McLean information systems success model (D&M IS Success Model (DeLone & McLean, 2003) the technology-organisation-environment framework (TOE) (Tornatzky & Fleischer, 1990), and the technology acceptance model (TAM) (Davis, 1989) were the foundation of the integrated research model, which was validated and tested using SEM in Chapter 5. According to Cherry (2020), an independent variable is one that a researcher manipulates or modifies but that is unaffected by other factors. The independent variables in the current study were SQ, KQ, EHR, IQ, PU, PEU, TC, and OC, while the mediating variables were BCP and DTD. In addition, each of these variables were statiscally tested to determine their influence on EBHP dependent variable in this study.

4.3 RESEARCH APPROACH AND METHOD

a). Research Approach

Saunders, Lewis, and Thornhill (2018 cited in Saunders et al., 2019) argue that there are three research approaches: deduction, abduction, and induction. Kilani and Kobziev (2016) relate the deductive approach to the quantitative research method and the inductive approach to qualitative research. According to Melnikovas (2018), the abductive and inductive approaches are normally used to develop theory, or they are used in fields of study where there is little research on the topic under investigation, whereas the deductive approach is applied to test an existing theory.

b). Deduction approach

Deductive reasoning is used to establish a research question or hypothesis, connect it to existing theory, and then gather evidence to support or refute the idea (Melnikovas, 2018). Bergdahl & Berterö (2015) assert that deductive investigation starts with the general and concludes with the specific. In other words, it moves from theory to data. According to previous research, the deductive logic of inquiry used in the quantitative approach typically involves moving away from specific facts and towards generalised theories or abstract scientific concepts (Park, Bahrudin, & Han, 2020). Deduction is a method of thinking that entails shifting from a narrow focus to a broad perspective (Saunders, Lewis, Thornhill, & Bristow, 2019). Deductive research methodology is used when a researcher creates hypotheses and implications based on prior knowledge of the topic under examination. The method of data collecting is determined by theoretical assumptions. The hypothesis is then supported or refuted based on the assumptions in light of real evidence.

c). Induction approach

According to Saunders et al. (2019), inductive reasoning is the process of developing a strategy employing case studies and observations to find ways to draw generalisations about the topic under consideration. Future inductive research should move from evidence to hypothesis or from the specific to the general, according to Bergdahl and Berterö's (2015) recommendations. The most common qualitative induction strategies, according to Kovács and Spens (2015), are those that begin with observations and finish with generalisations (Butnaru, 2015). The inductive method quickly generates theories, according to Hibbert et al. (2014) and Bergdahl & Berterö (2015); as a result, it cannot be used to establish theories or hypotheses or to rationalise facts. To examine occurrences and develop theories or hypotheses, e-health first uses empirical research or studies (Aslam et al., 2016).

d). Abductive approach

According to established ideas, abduction starts with an odd, irregular, or unexpected observation and then manages the consequences of the discovery (Brandt & Timmermans, 2021). Conception integration, which does not occur in the context of a consistent language, is a crucial aspect of abduction since the generation of new hypotheses is connected to new theoretical advancements (Bryman & Bell, 2015). In this study, deduction approach was adopted to identify the critical success factors for the implementation of EBHP at a South African public hospital.

4.5 RESEARCH METHOD

Methods are "approaches or techniques for collecting and interpreting data related to a study issue or hypothesis," according to Mukhles (2020). There are three categories of research methods: quantitative, qualitative, and mixed; this study employed a quantitative method, in accordance with (Saunders et al., 2019; Creswell, 2018). A quantitative analysis assesses the relationship between variables to unbiasedly test hypotheses. The numerical outcomes can then be examined using statistical techniques (mean, standard deviation, regression, and structural equation modelling). According to Creswell (2018), quantitative investigations deductively evaluate hypotheses utilising current data by constructing and building hypothetical relationships and suggested results, all of which contribute to the discovery of scientific findings.

According to Bryman & Bell (2018), the quantitative approach not only makes it possible to assess the truthfulness of pre-existing theories but also gives the study the necessary validity to measure hypotheses and assess data more quickly. The survey questionnaire's validity and reliability were also examined, and both were found to be highly significant. This is consistent with Bryman & Bell's (2018) assertion that using a quantitative data analysis approach can help researchers balance the development of their work by addressing the reliability and validity of ideas. As already mentioned, a questionnaire was selected as the method of data collection and was developed based on TOE, TAM, and updated D&M IS Success Model constructs which were integrated to develop the study's conceptual framework.

4.4 SETTINGS OF THE RESEARCH AND TARGET POPULATION

4.4.1 Target population

According to Grove, Burns, and Grey (2013), the research setting is the site where a study is carried out. This research study was conducted at Dr George Mukhari Academic Hospital (DGMAH): a tertiary academic hospital affiliated with the Sefako Makgatho Health Sciences University (SMU) (previously MEDUNSA) in the Gauteng province of South Africa. Numerous departments are located within the hospital, including those for family medicine, dermatology, cardiology, neurology, haematology, renal or nephrology and intensive care unit (ICU), general surgery, neurosurgery, cardiothoracic, ophthalmology, ENT, plastic surgery, urology, maxillofacial surgery, transplant unit, paediatrics, paediatric surgery, neonatal unit, orthopaedics, and gynaecology. SMU and other nursing schools in Pretoria train their students at this hospital.

According to Cooper and Schindler (2014), Neuman, (2014) a population is the total set of constituent components from which the researcher wants to derive conclusions. Zikmund, Babin, Carr, and Gryphon (2016) define the target population as the entire group that possesses the relevant demographic characteristics for the study activity. The study's target population included healthcare professionals (medical physicians, nurses, pharmacists, radiologists, and radiographers).

4.4.2 Sampling techniques and sample size

The sampling strategy for the current study involved selecting a manageable number of participants from the study's target group (Denscombe, 2014). Saunders, Lewis, and Thornhill (2016) assert that there are no restrictions for non-probability sampling methods other than quota sampling and that the problem of sample size is ambiguous. Nonprobability, often known as a judgement or convenience sampling approach, was used in the study. According to Etikan, Alkassim, and Abubakar (2016), Setia (2016), Elfil and Negida (2017), convenience sampling is a non-probability sampling technique that chooses people of the target population who are present in the area at a particular moment. This sampling method involves the researchers' enrolling respondents based on their availability and accessibility. For this reason, this strategy is easy, reasonable, and useful. Convenient sampling refers to the process where the researcher selects the sample components based on their proximity and ease of access (Gravetter & Forzano, 2012). Deliberate sampling has some limitations, such as a decreased degree of generalisability, a smaller range of data analysis techniques, and a higher likelihood that researchers will choose the incorrect inclusion criteria (Haegele & Hodge, 2015; Palinkas, Horwitz, Green, Wisdom, Duan & Hoagwood, 2013).

Convenience sampling is used to collect data from people who are willing to participate in a study, approachable, or otherwise make it easy for the researcher to contact the participants (Wienclaw, 2019). The researcher was able to locate respondents who matched the study's inclusion criteria, which included every healthcare professional, using the convenience sample technique. Furthermore, the researcher was unable to apply random sample due to time restraints and Covid 19 lockdown regulations. However, the respondents were given the questionnaires and told to complete them whenever it was convenient for them within a period of two weeks. Convenience sampling was deemed acceptable because the convenience sample for this study was chosen from the easily accessible population of healthcare professionals at DGMAH in the province of Gauteng.

4.4.3 Sample size

Researchers must determine the necessary sample size to conduct meaningful research. Furthermore, before deciding on the sample size, the type of statistical analysis should be considered. Exploratory factor analysis (EFA) and structural equation modeling (SEM). The two analyses used in SEM were the structural model and confirmatory factor analysis (CFA). Researchers should conduct EFA and CFA using separate datasets, according to Schumacker and Lomax (2016) and Kline (2016). Schumacker and Lomax (2016), further noted that, "a researcher could start model development by conducting exploratory factor analysis (EFA) on a sample of data to establish the quantity and type of latent variables in a plausible model." Once a reliable model has been identified, confirmatory factor analysis (CFA) can be used to test or confirm it on a larger sample of data.

The total number of observed variables is multiplied by five to determine an appropriate number of participants in EFA (Hair et al*.,* 2019). Numerous academics contend that the sample size for EFA should be at least 100 participants (Fabrigar & Wegener, 2012; Gorsuch, 1983). Sample sizes of 100 to 400 are suitable for SEM, however (Anderson & Gerbing, 1988; Boomsma, 1983). Hair et al. (2019) recommends 200 participants for SEM analysis. SEM was utilised in this investigation because it works well with high sample sizes. According to Kline (2011), a large sample size guarantees repeatable static results. SEM requires 200 samples at a minimum, according to Green and Salkind (2016). A sample size of 200 or above in SEM produces favourable outcomes. For this study, a sample size of 470 respondents was deemed adequate.

4.5 DATA COLLECTION METHOD

There are numerous data collection techniques that can be categorised as qualitative or quantitative, including interviews, questionnaires, focus groups, and observations (Bell et al., 2018; Creswell and Creswell, 2017; Easterby-Smith et al., 2018). The choice of an appropriate method for data collection is influenced by a number of variables, including the duration of the study, the resources available to the researcher(s), the level of accuracy anticipated for the study, the researcher(s)' level of expertise, and the costs associated with each specific method. According to Sekaran and Bougie (2016), a quantitative method is one in which numerical data are generated or used as a result of a data analysis strategy (such as through statistics or graphs) or a data gathering method, such a survey employing a questionnaire.

Creswell and Creswell (2017) define a survey as a method used to gather a quantitative or numerical description of the opinions, attitudes, or trends within a population through the analysis of a smaller sample of the broader population. A key advantage of questionnaire surveys, according to Bell et al. (2018) and Collis and Hussey (2014), is their ability to precisely, efficiently, and extremely cheaply collect data from a huge research sample. Questionnaire results are uniform and simple to conduct and compare. The majority of the time, questionnaires produce data that is very accurate and valid (Bell et al., 2018). Most survey questionnaire results are representative of the entire population, making it possible to extrapolate findings from a sample to the full population (Creswell & Creswell, 2017). For this study, data was collected from DGMAH healthcare professionals using a closed-ended questionnaire.

4.5.1 Instrument design and development

The literature review, as well as the proposed conceptual framework in Figure 3.2, served as the basis for the questionnaire developed for this study. Technology acceptability studies commonly include questionnaires (Lew, Lau, & Leow, 2019). It enables researchers to gather data that captures a group's attitudes and behaviours (Queirós, Faria, & Almeida, 2017). There were three sections to the survey: the first section comprised questions concerning the participants' sociodemographic characteristics. The survey featured multiple-choice questions. These are the most prevalent queries, according to Malhotra and Dash (2011). To avoid incorrect responses and improve the data's trustworthiness, the background information was provided in the second portion (Saunders et al., 2019).

According to Creswell (2019) and Croasmun and Ostrom (2016), the built-in questionnaire mostly collected quantitative data and allowed respondents to answer closed-ended questions in numerical order. In earlier research studies on this subject, a straightforward three-point scale (1–3): 1 = No, 2 = Yes and 3 = Not Sure was employed in addition to the one utilised in this study (Creswell, 2018). Questions about the key success of evidence-based healthcare practice implementation were asked in the third section of the questionnaire. These statement items originated from the conceptual model presented in Figure 3.2. The modified D&M IS Success Model, the TOE framework, and the technology acceptance model (TAM) served as the foundation for the development of the statement items. A five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used to evaluate the statement items.

4.5.2 Construct operationalization

According to Cohen, Manion and Morrison (2018), operationalisation is the act of stating the overarching purpose of the questionnaire and translating that goal into a detailed set of objectives. Foschi (2014) defines operationaliation as the process of turning vague ideas into concrete, quantifiable results. When the operationalisation of the questionnaire is finished, the next step comprises developing the actual study questions that must be addressed (Cohen et al., 2018). The operationalisation of the study constructs is discussed in this section.

Independent variables:

Measurement scales for electronic health records (EHR) construct

EHR adoption satisfies the demands of a variety of healthcare industry stakeholders, including physicians, patients, medical staff, insurance companies, and legislators (Aminpour, Sadoughi & Ahamdi, 2016). A few of the many advantages that the digitization of patient records offers to medical professionals include automated reminders to prevent medication errors. Improved information sharing across the medical healthcare professionasl, and increased transparency by ensuring complete and legible documentation of the patient's condition. (Meeks et al., 2014). In order to operationalise the variable, mandate measurement from Cheung, van der Veen, Bouvy, Wensing, van den Bemt, and de Smet's (2014) research was used. These items were used in this study to assess the influence and impact of electronic health records (EHR) on evidence-based healthcare practice (EBHP) and these constructs items are represented as EHR1–EHR6. The modified construct items in Table 4.10 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.10: Likert scale items (Electronic Health Records) construct

Construct	Construct item	Description
Electronic health records (EHR)	EHR1	I'm certain that the EHR reports will be easier to generate.
	EHR2	I believe generated reports from EHR will be accurate.
	EHR3	I believe it will take short time to generate a report using EHR.
	EHR4	I will accept as true that EHR will enable faster patient communication and delivery of care.
	EHR5	I believe EHR will increase data security and confidentiality.
	EHR6	EHR will enable the capturing of demographic and clinical health information.

Measurement scales for knowledge quality (KQ) construct

Table 4.1: Likert scale items (Knowledge Quality) construct

Construct	Construct item	Description
Knowledge quality (KQ)	KQ1	I will accept as true that using an EHR system will ensure that the healthcare professionals have the knowledge base necessary to understand the patient condition.
	KQ2	I am certain that using an EHR system will enable the facilitation of better patient care decision-making.
	KQ3	I believe by using an EHR system the sheer volumes of data will improve the treatment quality since it will be easily shared among medical healthcare professionals.
	KQ4	I believe by using an EHR system the sheer volumes of data will improve the treatment quality since it will be easily shared among medical healthcare professionals.
	KQ5	I am certain that using an EHR system will accelerate delivery times for patients.
	KQ6	I believe that using an EHR system will communicate important information widely and quickly.

Knowledge management can be employed as a technique to increase the quality of the services provided by healthcare organisations (Li et al., 2020). Haughom (2014); Magaireah, HidayahSulaiman and Ali (2019) all emphasise the importance of knowledge access for problem-solving and well-informed healthcare decision-making. Previous studies by Alhalhouli, Hassan and Der (2014); Dessie (2017); Lee (2017) used the following items to measure the knowledge quality construct. The items are used in this study to assess the impact of EHR on knowledge quality and the construct items are represented with KQ1–KQ6. All modified construct items in Table 4.1 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for medical error reduction (MER) construct

Table 4.2: Likert scale items (Medical Error Reduction) construct

Construct	Construct item	Description
Medical error reduction (MER)	MER1	I am certain that using EHR will reduce errors found within personal health records.
	MER2	I believe using EHR will improve patient management by reducing medical errors.
	MER3	I believe using EHR will provide up-to-date information about the patient.
	MER4	I believe using EHR will provide medical healthcare professionals with the ability to share patient data.
	MER5	I believe using EHR will provide sufficient information about patients' well-being.
	MER6	I will accept as true that using EHR will solve the problem of illegible handwriting of health care providers.

Knowledge management can lower medical errors and consequently associated costs by giving practitioners decision support (Alhalhouli, Hassan & Der, 2014). It is well known that the quality of medical diagnoses and decisions is significantly impacted by the tacit knowledge sharing among health professionals, such as the sharing of clinical experiences, skills, know-how, or "know-who" (Sabeeh, Mustapha & Mohamad, 2018). The following construct items for assessing medical error reduction (MER) are presented by Sabeeh *et al.* (2018) in their study for operationalising the variable. These items are used in this study to assess the impact of EHR on medical error reduction and these construct items are represented with MER1–MER6. The modified construct items in Table 4.2 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for service quality (SQ) construct

The level of excellence of health services within the purview of the hospital is the level of excellence of health services for the community to meet the patient's needs for healthcare while adhering to acceptable, efficient, and effective use of resources and service standards (Giao et al., 2020; Pham & Vu, 2020). In their study, Thomas, Costa and

Oliveira (2016) propose the following items for measuring service quality (SQ) variables in order to operationalise the variable. These construct items are used in this study to assess the influence and impact of EHR on service quality and are represented with SQ1–SQ6. All modified construct items in Table 4.3 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.3: Likert scale items (Service Quality) construct

Construct	Construct item	Description
Service quality (SQ)	SQ1	I believe by using an EHR system, the support services for the system will be dependable.
	SQ2	I believe by using an EHR system, the support services will give me patient individual attention.
	SQ3	I believe using an EHR system will overall enable the support services to meet my needs.
	SQ4	I'm certain that using an EHR system will provide more rapid access to patient data than paper-based records.
	SQ5	I believe that using an EMR system will be useful in managing patient care in my practice.
	SQ6	I believe that using an EHR system will improve the service productivity of healthcare professionals.

Measurement scales for information quality (IQ) construct

Existing literature has emphasised the advantages of deploying EHR, such as increased patient safety measures, improved patient outcomes, and lower costs (Meeks et al., 2014). According to Krist, Beasley, Crosson, Kibbe, Klinkman, Lehmann, and Waldren (2014), the implementation of an EHR system may encourage the coordination of patient care among doctors and the sharing of clinical data, which may lead to patients obtaining higher-quality care. The following items were used in past studies to measure the attributes of information quality [IQ] (Al Alawi, Al Dhaheri, Al Baloushi, Al Dhaheri & Prinsloo, 2014; Mantas, Househ & Hasman, 2014). These items are used in this study to assess the impact of EHR on information quality (IQ) and these construct items are represented with IQ1–IQ6. The modified construct items in Table 4.4 were measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.4: Likert scale items (Information Quality) construct

Construct	Construct item	Description
Information quality (IQ)	IQ1	I believe using EHR will provide patient accurate and up-to-date information.
	IQ2	I will accept as true that using EHR will provide information from the system that will be relevant to my work.
	IQ3	I'm certain that using EHR, the information I will get from the system will be accurate.
	IQ4	I believe using EHR it will be easy to understand patient information derived from the system.
	IQ5	I believe using EHR the information will be presented in a useful format.
	IQ6	I believe using EHR will enable medical healthcare professionals to share patients' records that will enhance information quality.

Measurement scales for perceived usefulness (PU) construct

Table 4.5: Likert scale items (Perceived Usefulness) Construct

Construct	Construct item	Description
Perceived usefulness (PU)	PU1	I believe using EHR would be useful in my professional activities.
	PU2	I believe using EHR would help to improve my patient care delivery.
	PU3	I believe using EHR would improve my job performance.
	PU4	I am certain that using EHR will make health information sharing easier and more effective.
	PU5	In my hospital, I believe using EHR will enable improved coordinated care between medical healthcare professionals.
	PU6	In my hospital, I believe using EHR will reduce medical errors.

Perceived usefulness (PU) is a measure of how much people think that adopting new technology would improve their ability to execute their jobs (Zhang et al., 2019). Furthermore, perceived usefulness measures how much people think using technology will help them to perform better (Saripah, Putri & Darwin, 2016). According to various empirical studies, PU is the crucial component of using a particular technology (Chow, Herold, Choo & Chan, 2012). The following construct items for assessing perceived usefulness are presented by Damnjanovic, Jedinak and Mijatovic (2015); Elkaseh, Wong and Fung (2016) in their study for operationalising the variable. In addition, these items are used in this study to assess the influence of perceived usefulness (PU) in the implementation of electronic health records (EHR) in public hospitals and these construct items are represented with PU1–PU5. All modified construct items in Table 4.5 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for perceived ease of use (PEU) construct

Table 4.6: Likert scale items (Perceived Ease of Use) construct

Construct	Construct item	Description
Perceived ease of use (PEU)	PEU1	I believe that EHR has the potential to improve the healthcare profession’s diagnostic endeavours.
	PEU2	I believe the use of EHR will make information dissemination more efficient.
	PEU3	I am certain that it will be easy for me to become skilful in using the EHR.
	PEU4	I believe using EHR will make it easier to adhere to hospital policies such as patient care documentation.
	PEU5	I believe an EHR system will increase my diagnosis accuracy
	PEU6:	I believe that in a short period of time, I will be an expert in using the EHR.

According to Zhang, Han, Dang, Meng, Guo and Lin (2017), perceived ease of use is the idea that utilising a specific technology will be simple and painless. PEU is a metric that assesses how user-friendly a user believes a particular technology to be (Kimathi & Zhang, 2019). The following items were used by Singh, Keswani, Singh and Sharma (2016), and Phan, Nguyen and Bui (2019) in their studies to operationalise the variable and measure normative pressures. These items are used in this study to determine the influence the perceived ease of use (PEU) in the implementation of electronic health records (EHR) in public hospitals and these construct items are represented with PEU1–PEU6. The modified construct items in Table 4.6 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for technical context (TC) construct

Table 4.7: Likert scale items (Technical Context) construct

Construct	Construct item	Description
Technical context (TC)	TC1	I believe EHR will provide electronic records for patients as well as demographic-related information.
	TC2	I will accept as true that EHR will provide electronic records for patient assessment / clinical notes.
	TC3	I believe EHR will provide electronic records for patients' financial- and fee-related information.
	TC4	I'm certain that EHR will enable the electronic ordering of laboratory tests.
	TC5	I believe EHR will provide electronic ordering of imaging tests (i.e., X-rays, CT scans, MRI scans, etc.).
	TC6	I believe EHR will provide practice administration information systems (i.e., appointment booking / patient scheduling systems).

The technological context encompasses all relevant technologies to the organisation, including both those that are already in use and those that are already available outside the company but have not yet been accepted (Ying & Lee, 2016). Due to their less varied industrial infrastructure, developing nations adopt information and communication technologies more slowly (Katurura & Cilliers, 2018). The probable lack of computer knowledge among users, according to Cohen et al. (2015), exposes a need for training and support for the improvement of skills across all areas of healthcare. The following items were constructed by Mohamadi, Noor, and Zhari (2014) and Mohamadli et al. (2017) to operationalize the variable and quantify the organisational technical aspects in their study. These items are used in this study to assess the influence and impact of technical context on the adoption of EHR at a South African public hospital and they are represented with Q1–IQ5. The modified construct items in Table 4.7 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for organisational context (OC) construct

Organisation context refers to describing the factors that determine an organisation, such as its size, the formalization, centralisation, and complexity of its management structure, as well as its channels of communication and decision-making (Angeles, 2014). Organisational change management is another factor that influences the success of IT installations (Dwivedi et al., 2015). Some researchers have stressed the significance of taking into account factors like changing organisational structure, people, processes, culture, and politics in order to ensure that IT initiatives are genuinely effective (Dwivedi et al., 2015). The following items are provided by Maduku, Mpinganjira, and Duh (2016); Mtebe, Nakaka, International and Alliance (2018) for measuring the construct in their studies to operationalise the variable. These items are used in this study to assess the influence of organisational context (OC) i.e., top management support on the adoption of electronic health records and these construct items are represented with OC1–OC6. The modified construct items in Table 4.8 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.8: Likert scale items (Organisational Context) construct

Construct	Construct item	Description
Organisational context (OC)	OC1	I believe with the support of top management and the Department of Health, EHR can be implemented in our public hospitals.
	OC2	I believe our top management will make an effort to convince other healthcare professionals of the benefits of EHR.
	OC3	I believe our top management will encourage other healthcare professionals to use EHR.
	OC4	I’m certain that our medical healthcare institution has the technological resources required to make use of EHR.
	OC5	I believe that public hospitals have the managerial resources to manage and support the use of EHR.
	OC6	I believe the Department of Health has the financial resources to make use of EHR in our public hospitals.

Measurement Scales for environmental context (EC) construct

The TOE framework's environmental context refers to all external factors that may help or hinder an organisation's adoption of new information technology (Baker,2014). External partners and their impact on organisations' technology adoption decisions are a crucial consideration in this context (Panagiotopoulos & Barnett, 2015). Studies on the adoption of information technology by hospitals have found a correlation between hospitals' propensity to adopt new technology and the level of competition they experience (Bolanne et al., 2020). The following items are suggested for measuring the construct in studies that adapt Wiedenhöfer and Keppler's (2014) work to operationalise it. These items are used in this study to assess the influence of environmental factors on the adoption of electronic health records (EHR) and these construct items are represented with EC1–EC6. The modified construct items in Table 4.9 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.9: Likert scale items (Environmental Context) construct

Construct	Construct item	Construct item description
Environmental context (EC)	EC1	I believe some of our healthcare professionals who are aware of the benefits of EHR will be happy to see its implementation in public hospitals.
	EC2	I believe the government should be at the forefront in driving the use of EHR systems in public hospitals.
	EC3	I believe government should demonstrate a strong commitment to promoting the use of EHR.
	EC4	I believe there are effective laws (e.g., with regard to the privacy of patient information) that support EHR.
	EC5	I will accept as true that healthcare professionals should have a strong influence on the EHR when implemented.
	EC6	I believe relationships with our patients will continue to suffer if EHR is not implemented in public hospitals.

Mediating variables:

When the association between the independent and dependent variables is surprisingly weak, inconsistent, or non-existent, the term " mediating variable" is used to describe the interaction (Abubakar & Ahmad, 2013). Knowledge quality KQ), electronic health records (EHR) information quality (IQ), and medical error reduction (EHR), the four independent constructs from the conceptual framework in Fig. 3.2, have been found to be influenced by mediating variables: better coordination of patient care (BCP), diagnosis, and treatment of diseases (DTD).

Measurement scales for better coordination of patient care (BCP) construct

Table 4.10: Likert scale items (Better Coordination of Patient Care) construct

Construct	Construct item	Description
Better coordination of patient care (BCP)	BCP1	I'm certain that using EHR will give me useful reminders that will help me to identify the change of care needs for my patients in a timely manner.
	BCP2	I believe using EHR will enable medical healthcare professionals and other healthcare providers to make sound clinical decisions in a timely manner.
	BCP3	I will accept as true that using EHR will enable patients to consult other medical healthcare professionals more easily.
	BCP4	I believe using EHR will reduce unnecessary patient transfers or referrals to other healthcare providers.
	BCP5	I'm certain that using EHR will reduce patients' costs of health services.
	BCP6	I believe using EHR will facilitate better patient care when it comes to decision-making.

It has been suggested that implementing and adopting an EHR system may enhance the ordering and reception of diagnostic pictures and lab tests, as well as eliminate errors, enhance documentation, and save time (Hasanain et al., 2015). Using an outpatient EHR or an integrated outpatient and inpatient EHR resulted in better care coordination between clinicians and delivery sites (Aldredge, Rodriguez, González & Burt, 2020). The adoption of the outpatient EHR was associated with improvements in the glycemic and lipid management of diabetic patients (Mostafa, 2019). Team cohesion and EHR use had a statistically significant interaction effect on clinical outcomes for diabetes patients and care coordination. In order to operationalise the variable in their research (Kahouei, Mohammadi, Majdabadi, Solhi, Parsania, Roghani & Firozeh, 2014). These items are used in this study to assess the impact of electronic health records (EHR) on better coordination of patient care (BCP) and these construct items are represented with BCP1–BCP6. The modified construct items in Table 4.11 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Measurement scales for diagnosis and treatment of diseases (DTD) construct

Table 4.11: Likert scale items (diagnosis and treatment of diseases) construct

Construct	Construct item	Description
Diagnosis and treatment of diseases (DTD)	DTD1	I will accept as true that using EHR have the capabilities to improve the accuracy of patient data, hence, fewer errors.
	DTD2	I believe using EHR will decrease healthcare professionals' time per patient encounter.
	DTD3	I'm certain that using EHR will provide rapid access to patient data compared to a paper-based record system.
	DTD4	I believe using EHR will improve the accuracy of clinical documentation.
	DTD5	I believe using EHR will enable evidence-based decision-making from assigned medical professionals.
	DTD6	I believe using EHR will shorten patient waiting times.

EHR, which has the ability to store health information such as test results and treatment information, is a patient's electronic equivalent of their paper medical record. According to Arndt et al. (2017), it is also intended to deliver real-time, patient-centered records that make information rapidly and securely accessible to the authorised users. An accurate and timely diagnosis is the foundation of any successful treatment (Aminpour et al., 2016). In addition, this crucial clinical decision-making is enabled by a well-structured, end-to-end EHR system. Based on the literature, six items were independently created to operationalise the variable (Kuo, Liu & Ma, 2013; El Mahalli, 2015; Van Hoeven *et al.,* 2017). These items are represented in this study to measure the impact of electronic health records (EHR) on the diagnosis and treatment of diseases (DTD) and these construct items are represented with DTD1–DTD6. The modified construct items in Table 4.12 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

4.5.3 Dependent variable

Measurement scales for evidence-based healthcare practices (BHP) construct

Evidence-based practice is necessary to enhance patient health outcomes (Warren et al., 2016). The advantages of electronic health records (EHRs) were established in a previous study (Berghout, Fabbricotti & Buljac-Samardzk, 2017). One of the most important components of knowledge management is knowledge sharing (Alhalhouli et al., 2014). Assuring efficient information transfer within the healthcare system is one of the top priorities for improvements in patient safety globally, according to Beigmoradi, Pourshirvani, Pazokian & Nasiri, (2019). In order to operationalise the variable, a study was done (Ayabakan, Bardhan, Zheng, & Kirksey, 2017). These items are used in this study to assess the influence of electronic health records (EHR) on associated constructs such as information quality (IQ), knowledge quality (KQ), service quality (SQ), medical error reduction (MER) and these construct items are represented with EBHP1–EBHP5. The modified construct items in Table 4.12 were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

Table 4.12: Likert scale items for (evidence-based healthcare practice) construct

Construct	Construct item	Description
Evidence-based healthcare practice (EBHP)	EBHP1	I believe the use of an EHR system will enable the reduction of healthcare costs.
	EBHP2	I believe the use of an EHR system will facilitate interactions with a medical healthcare professional team.
	EBHP3	I accept as true that the use of an EHR system will allow healthcare professionals to have easy access to patient medical records.
	EBHP4	I believe the use of an EHR system will be efficient in providing excellent healthcare service.
	EBHP5	I believe the use of an EHR system will result in the reduction of medical errors.

The next section focuses on the pilot study, validity, and reliability of the self-administered questionnaire.

4.5.4 Pilot study

According to Creswell (2018), a pilot study can help get rid of any pointless inquiries that might arise during the main inquiry. The pilot testing for this project also serves a variety of purposes, such as ensuring that both the general approach and design and the actual questionnaire items are appropriate (Creswell, 2018). Different strategies might be used to implement questionnaires. For gathering data, face-to-face questionnaires that offer the opportunity to present the questions verbally, paper-and-pencil varieties that use items presented on paper, and computerised questionnaires are all options (Kabir, 2016).

In addition to using them online, over the phone, and even by posting, questionnaires can also be used. Although an online survey is a cost-effective choice, you should consider the probability of missing samples because of internet connectivity issues. These types allow for the use of many online survey services that offer questionnaires for the purpose of research, after which the obtained data can simply be added to the analysis software (Taherdoost, 2021). Securing ethical considerations, like as participant confidentiality, should be a priority in all these decisions. However, participants must try to provide concise and courteous responses to the queries (Kabir, 2016). Face validity was preserved because of the method used during this study's essential piloting phase.

The purpose of this pilot study was to assess the survey instrument that will be utilised for the actual data collecting in the large-scale investigation. Nashwa (2018) argues that when piloting a study, a researcher needs to consider a few crucial elements to make sure the instrument used is suitable for gathering useful data. These include determining which approaches are most useful for addressing the research objectives and calculating the time and materials needed to complete the larger final version of the study. 80 healthcare professionals, mostly from the Tshwane District Hospital, including nurses, doctors, physicians, dentists, midwives, radiographers, chemists, physiotherapists, and optometrists, were selected for this pilot study to test the usability of the questionnaire. Drop-and-pick later was the method used to distribute the questionnaires, and this was before the Covid 19 pandemic. A maximum of two weeks was given to the respondents to fill in the questionnaires. Out of the 80 questionnaires administered only 60 were usable for the pilot study. Following the pilot study, a few changes were made to the questionnaire.

4.5.5 Validity and reliability of self-administered questionnaire

Evaluating the research tool's reliability and validity is crucial. Sekaran and Bougie (2019) assert that a measuring instrument's dependability can be determined by how consistently it captures the subject of the inquiry. According to Heale and Twycross

(2015), while an exact level of reliability cannot be calculated, its estimate can be obtained using three criteria: homogeneity, stability, and equivalence. Validity and reliability measures are covered in further detail in the following section.

i. Validity

The validity of an evaluation instrument is determined by its application. It confirms that the evaluation tool measures what it intends to measure. It ensures that the instrument adheres to the theoretical concept (Ntshonga, 2019). Validity is determined by the reason for which an instrument is employed. The correctness of a test result is what is meant by the term "validity" (Karakaya-Ozyer, 2018). The coverage of the real data from the gathered or processed dataset is a measure of a research tool's or dataset's validity; therefore, establishing validity is crucial (Taherdoost, 2018). In the case of SEM analysis, it provides scientists with proof that the findings are reliable. Internal validity (credibility) and external validity are both essential components of research validity (transferability). However, it should be noted that the methods or approaches used in qualitative research to address validity and reliability differ from those used in quantitative research. Internal validity refers to the guided options in a research study that allow respondents to confidently choose the best option (Gunawan & Huarng, 2015). This assurance comes from the study's potential elimination of confounding variables. Huarng and Gunawan (2015). However, external validity looks at how much data and theories from one study can be applied to another.

Heale and Twycross (2015) used the following three types of evidence to show construct validity. The homogeneity test, which demonstrates that relationships between variables should be consistent across all tests, comes first (Van der Gaag, De Ruiter & Kunnen, 2016). Convergence serves as the second piece of construct validity evidence. In other words, convergent validity examines whether the measurement is connected to variables that should be connected if the instrument were valid. This occurs when different instruments measure the same concepts Cohen, Manion & Morrison, 2018). The final construct test, theory evidence, indicates whether the construct being measured exhibits behavior consistent with the theoretical claim (Heale & Twycross, 2015).

ii. Reliability testing

The purpose of reliability is defined “as the ability to repeat a research technique and obtain identical results each time”; it also relates to the precision and consistency of research tools, data and conclusions (Mbane, 2017). This study uses a variety of data collection and analytical techniques to produce accurate results (Saunders & Lewis, 2018). The required datasets were tested using the Cronbach's alpha (α) statistic to determine internal reliability. It is necessary to assess the measurement model's internal, convergent, and discriminant validity (Omar, Razak, Yasin, & Dauwed, 2018). One of the most important metrics used to evaluate reliability is the Cronbach's coefficient test, which determines whether the variables in the measurement model have consistent responses (Pallant, 2016).

Increased inter-item dependability is typically indicated by higher coefficients (closer to 1), which leads to a better measurement tool. In contrast, if an instrument's coefficients are lower than 0.70, it is thought to be less reliable. (Tavakol & Dennick, 2011, Saunders *et al.,* 2015). Therefore, to assess the internal consistency of the measure items in the questionnaire for the current study, Cronbach's coefficient alpha (α) was computed for the 13 constructs using *SPSS (Version 23.0).* Section 5.4 provides a summary of these findings regarding the 13 constructs' reliability and internal consistency (Table 5.10–Table 5.22).

4.6 MAIN SURVEY

Lockdowns and social distancing regulations have a variety of effects on clinical and public health research, especially when they are not connected to COVID-19. The COVID-19 pandemic had an impact on data collecting. From the beginning, the hospital where the data was collected followed the strict Centres for Disease Control and Prevention (CDC) guidelines. There was no bias because of the self-administered nature of the questionnaires (Polit & Beck, 2017). However, Christensen, Ekholm, Glümer, and Juel (2014) report a generally low response rate in self-administered questionnaires, which may be because there was no interviewer present to encourage participants to participate. However, it is also claimed that self-administered techniques produce higher-quality data since participants are more forthcoming, particularly when a delicate subject is raised (Polit & Beck, 2017). Following ethical approval and gatekeeper approval from the various stakeholders in accordance with annexures 1, 2, and 4, data was collected.

Participation by the respondents was entirely voluntary. They signed a consent and agreement form before the data gathering process. A self-administered questionnaire was given to the available healthcare personnel, who had 15-20 minutes to complete it. Those who had the time did so instantly, while others were requested to forward the surveys to their ward supervisors. Ward managers received A4 khaki envelopes to insert the completed questionnaires and were also given additional questionnaires to distribute. A total of 456 questionnaires were administered to DGMAH medical healthcare professionals. The survey received responses from 370 after seven (7) weeks and 300 were included in the analysis. However, information in some sections of the 70 questionnaires was not completed. These questionnaires were therefore excluded from the final analysis. Table 4.14 shows the number of questionnaires that were distributed and the response rate. *SPSS (Version 23.0)* was used to code the questionnaire. Each survey question was entered into SPSS as a variable with the appropriate coding options. A five-point Likert scale (1 = strongly disagree to 5 = strongly agree) was used to evaluate the statement items.

Table 4.13: Number of distributed questionnaires and participation rate

	Reaction	**Questionnaires Usable**	**Usable/Unusable rate %**
Total number of questionnaires distributed (370)	Accepted 370	Usable: 300	98.3%
	Rejected 70	Spoiled: 70	1.7%

4.7 ANALYSIS TECHNIQUES AND PROCEDURES

The methods for data analysis used in this study are discussed in this section. Preliminary data analysis, EFA and SEM were all used in this study. The required statistical analyses were carried out using the *AMOS (Version 23.0)* and the *SPSS (Version 23.0) software.* The details of each statistical analysis are covered below.

4.7.1 Preliminary data analysis

Data screening was done as the first step in the data analysis process to make sure the data was accurate and relevant. The four main problems in preliminary data analysis are missing data, outliers, non-response bias, and normalcy (Mustillo & Kwon, 2015; Tabachnick & Fidell, 2016). There are gaps in the data when respondents abandon the survey. Outliers are responses that deviate in some way from the rest of the data. Data that has been purposefully skewed is referred to as "non-response bias." Data distribution is referred to as "normality”, which examines whether the distribution of the data is "normal" or not.

4.7.2 Missing data

Data collection is constantly concerned with missing data, which could reduce the statistical validity of a study's conclusions (Vieira, 2017). In addition, data imputation should be used for any elements that have less than 15% of the data missing, according to Hair et al. (2019). To ensure that the dataset is complete, imputation is the process of giving each missing response a suitable value. Missing values can result in incorrect statistical analysis and interpretation of data (Armitage, Godzien, Alonso-Herranz, López-González, & Barbas, 2015). The discussion of missing data and how it was handled is covered in detail in section 5.2 of this study.

4.7.3 Outliers

The two types of outliers that marketing academics and social scientists focus on in their core data are univariate and multivariate outliers. Univariate outliers are outliers that only affect one variable. Multivariate outliers, on the other hand, are scores that exhibit an unusual pattern across several factors (Mertler & Reinhart, 2017). Univariate outliers are variables with standardised values (z-scores) greater than 48 but less than +4, or less than -4. (Hair et al., 2019). Any data with univariate outliers of less than 2% of the entire sample, according to Cohen, Cohen, West, and Aiken (2003), should be kept. According to Stevens (2001), the Mahalanobis distance is a well-liked statistical method for locating multivariate outliers. It is related to degrees of freedom and has threshold values of 3.5

or 4.0, according to Hair et al. (2019). Multivariate outliers need to be eliminated in contrast to univariate outliers.

4.7.4 Non-response

When there are systematically different responses from those who choose to participate in the research and those who choose not to, this is known as non-response bias. Avoiding non-response bias has two advantages. To begin with, the lack of non-response bias shows that the sample fairly represents the population (Robert Greszki, Marco Meyer & Harald Schoen, 2015). Second, the absence of non-response bias demonstrates that the quality of the dataset was not compromised by the multiple imputation technique (Mustillo & Kwon, 2015). Although non-response bias should be avoided, it can be difficult to collect data from non-respondents. As a result, researchers have developed techniques for searching for non-response bias evidence in collected data. An independent sample t-test is recommended by Armstrong and Overton (1977) to compare the mean responses of early and late groups of samples. When the means are noticeably different, the non-response bias is demonstrated.

4.7.5 Normality

Two measurements are used to assess the regularity of data distribution: skewness and kurtosis. Kurtosis refers to a distribution's peak, whereas skewness refers to its symmetry (Tabachnick & Fidell, 2016). When the skewness and kurtosis values are between -3 and 3 and -8 and 8, respectively, a normal distribution is attained (Kline, 2016). Data transformation can be used to handle non-normal distributions. Data transformation is a method for converting non-normal variables into a normal state (Hair et al., 2019). The following data transformations are available: square root, logarithm, inverse, squared, cubed, reflect and square root, logarithm, and inverse, and reflect and logarithm (Hair et al., 2019; Tabachnick & Fidell, 2016). Researchers can choose the best data analysis approach for their study, and the methodologies used in this study are covered in more detail in the next section.

4.8 EXPLORATORY FACTOR ANALYSIS

Following the descriptive analysis, the entire data set for this investigation underwent exploratory factor analysis (EFA), utilising maximum likelihood and Promax rotation. Chapter 6 will discuss the analyses' findings. In this study, the data was analysed and the relationships between the variables were tested using confirmatory factor analysis (CFA) and structural equation modelling (SEM) techniques. SEM and CFA were performed using the structural equation modelling software AMOS and the statistical data analysis software SPSS. The multivariate statistical analytic technique known as structural equation modelling, or SEM for short, is used to depict a network of complex structural relationships between one or more measurable variables and latent constructs. Confirmatory factor analysis (CFA) is also used to verify the factor structure of a set of observed variables (Hair et al., 2019).

Even though all the scales were derived from earlier research, EFA was used to ensure that the variables were classified into the correct components according to the theory. The model proposed associations between the dependent variables: BCP, EHR, MER, IQ, EBHP and the independent variables: SQ, KQ, PU, PEU, TC, OC, and EC. Given that certain requirements must be satisfied for data to be acceptable for factor analysis and structural equation modelling (SEM) (Holmes-Smith, 2011; Gaskin, 2012; Gaskin & Lowry, 2014; Hair et al, 2019), the first step in the EFA was to evaluate the data set for suitability before moving on to the next stage.

4.8.1 Factor analysis

The sample correlation matrix was assessed to determine its suitability before EFA began (Gaskin, 2012; Holmes-Smith, 2011). Hair et al. (2019) stated that the correlation coefficients needed to be at least 0.30 for the data to qualify for EFA. Items with a correlation coefficient of less than 0.30 should be eliminated because they have a weak correlation with the other factors (Holmes-Smith, 2011; Tabachnick & Fidell, 2019). Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) sampling adequacy metric were also used. KMO evaluates the accuracy of the correlations between the variables and is required to show that an underlying factor structure exists. The KMO index ranges from 0 to 1, with a value of at least 0.50 and 0.8 to 0.9 being preferred for EFA. The correlation matrix is compared to the identity matrix using Bartlett's test, and EFA must exist if the correlation matrix is significantly different from the identity matrix at $p < 0.05$ (Holmes-Smith, 2011).

4.8.2 Extraction

Extraction of the components that best defined each metric was the next step after deciding whether the data was appropriate for EFA. An EFA with SPSS and maximum likelihood extraction with Promax rotation were used to achieve this. These methods were chosen because they are frequently used to help with output interpretation (Holmes-Smith, 2011). The "total variance explained" output, which shows the components, their loadings, and the variance (or "eigenvalue") for each factor, was the first output to be examined. To accurately represent the items, factors must have eigen values greater than one (1) and a total variance greater than 60%. In addition, even though this is a frequently used metric, Cattell (1966) and Holmes-Smith (2011) recommended adding a scree plot of the eigenvalue values for each factor and extraction of any components before the scree plot, both of which were done in the current investigation.

To identify and eliminate any items with low loadings, cross-loadings, or unexpectedly negative loadings, the pattern matrix was examined based on the theory supporting the dataset by looking at the factor loadings, which represent the correlation between the factor and the variable. To ensure effective analysis, items with loadings less than 0.3 were removed, and the data was repeated (Allen & Bennett, 2010). The internal consistency of the scores from each scale on the components that emerged from the EFA was evaluated using Cronbach's alpha (Cronbach, 1951). Chapter 5 discusses the emerging factors, factor-structure loadings, Cronbach's alpha, extracted variances, and eigenvalues.

4.8.3 Confirmatory factor analysis

The CFA technique makes it feasible to determine correlations between observed indicators and hidden variables (or latent constructs) by producing links between scores for measuring constructs (Hair et al., 2019). The validity of the measurement model was investigated in this study utilising a CFA using *AMOS (Version 23.0).* This study used both the construct validity and goodness-of-fit indices, which Hair et al. (2019) identified as the two steps for assessing CFA validity. However, a test run was conducted to enhance the model before the two steps and based on the standards suggested in the literature, the techniques for improvement were put into practice. According to Kline (2016), model refinement processes are necessary for the model to be improved and re-specified to increase its discriminant validity and produce a better model fit.

According to Argyrous (2011), model improvement can be carried out by relating indicators to various elements or by eliminating them, as well as by using measurement errors that are associated or by relating indicators to several distinct factors. In addition, reviewing the modification indices (MIs), the standardised residuals, and the searches of specification may aid in enhancing the model's goodness of fit (Hair et al., 2018). The model's improvement was consequently influenced by four variables. First, according to Hair et al. (2019), only indicator variables with a standardised regression weight greater than 0.50 were kept. In addition, according to Hair et al.'s (2019) findings, indicator variables with squared multiple correlations lower than 0.30 had to be disregarded.

4.9 STRUCTURAL EQUATION MODELLING

The aim of the study was to develop a structural equation model for evidence-based healthcare practice (EBHP) at a South African public hospital. The final stage of data analysis in this study involves the assessment of the validity of the structural equation models (SEM). In relation to this, the corresponding hypothesised theoretical relationships are examined. Malhotra (2010) suggests following a six-step approach to doing a good SEM study. This involves:

- defining the various constructs,
- developing and specifying the measurement model,
- evaluating the measurement model's construct validity and reliability,
- establishing the structural model,
- analysing structural model fit and
- drawing conclusions.

Anderson and Gerbing (1988) on the other hand, propose a two-stage SEM approach. This includes:

- evaluating the structural model to see the causal relationships between the underlying exogenous and endogenous constructs using parameter estimates and
- evaluating the measurement model to specify the causal relationships between the observed variables and confirm the goodness of model fit.

4.9.1 Assessment of the model fit (goodness of fit)

Diamantopoulus and Siguaw (2006) describe the model fit evaluation as the degree to which the hypothesised model fits the obtained data. The standardised residuals covariance and modification indices (MI) which reveal the associated error among the items when two or more items are redundant to each other are examined as part of the assessment. Items with a high MI value and a residual value higher than the 2.58 criterion ought to be eliminated (Field, 2016; Awang, 2012; Hair *et al.,* 2019; Diamantopoulus & Siguaw, 2006). In SEM analysis, the goodness of fit (GOF) of the model is calculated by evaluating its fit using a variety of fit indices. Table 4.14 shows the summary of the goodeness-of-fit test.

Table 4.14: Summary of goodness of fit (GOF) indices

Category	Name of Index	Threshold	Comments
Absolute fit	Chi-square (χ2)	p > 0.05	Indicates exact fit of the model. A non-significant *p*- value indicates an adequate representation of the data. This measure is sensitive to large sample size.
	Goodness of Fit (GFI)	≥ 0.90	Value close to 0 indicates a poor fit, while value close to 1 indicates a perfect fit.
	Root Mean Square Error of Approximation (RMSEA)	≤ 0.08	Values less than 0.05 are generally considered a ‘good’ fit. Values between 0.05 and 0.08 are considered ‘adequate’ fit. Values up to 0.10 are considered acceptable represent the lower bound of fit.

	Standardised Root Mean Square Residual (SRMR)	< 0.08	The smaller, the better; 0 indicates perfect fit
Incremental fit	Adjusted Goodness of Fit (AGFI)	> 0.80	Value close to 0 indicates a poor fit, Value close to 1 indicates a perfect fit.
	Tucker-Lewis Index (TLI)	≥ 0.90	
	Comparative Fit Index (CFI)	≥ 0.90	
Parsimonious fit	Normed Chi-square (χ2/df)	1.0 ≤ χ2/df ≤ 5.0	Lower limit is 1.0, upper limit is 3.0 or as high as 5.0

Table 4.14 states that three categories are used to assess a model's fit: absolute fit, incremental fit, and parsimonious fit of four to six indices. According to the study, there is disagreement among academics on which indices are the most important and should be reported, though (Hair et al., 2019; Kline, 2016). This means that it depends on how the researchers interpret their results; nonetheless, some researchers advise using at least one index per category (Hair et al., 2019).

4.9.2 Regression analysis

Regression analysis aims to demonstrate the influence independent factors may have on the dependent variable. In addition, it can reveal the extent to which the independent variables can account for the variance in the dependent variable (Pallant, 2016). Further, regression analysis can be used as a supplement to the structural model in CFA to examine each item's contribution to the dependent variables. However, two separate regressions are required to examine both the predicator's and the dependent variable's influence. It is possible to find the standardised beta coefficient using regression analysis. The magnitude of each independent variable's influence on the dependent variable is depicted by this coefficient. As the absolute value readings climb, the effect gets stronger. The standardised beta coefficient must be significant, and the significance threshold must not be higher than 0.5 for the outcome to be satisfactory (Freedman, 2013).

4.10 ETHICAL CLEARANCE CONSIDERATIONS

Ethics refers to the standard that distinguishes morally righteous behaviour from immoral behaviour and vice versa (Resnik, 2020). This study's use of ethics as a guiding principle establishes moral guidelines that all researchers must adhere to throughout the research process (Adhikari, 2020). Its main objective, the pursuit of knowledge and truth, is supported by the research standards. Furthermore, research ethics forbids a variety of behaviours, including lying and cheating (Adhikari, 2020). Permission to conduct the study was sought from the University of South Africa's College of Agriculture, Environmental and Environmental Sciences (CAES) General Research Ethics Review Committee (see Appendix A).

Furthermore, DGMAH's executive manager gave his consent (see Appendix D). The researcher provided written information detailing the study's objectives to each participant (see Appendix B). The study was voluntary, anonymous, and confidential, and participants were free to leave at any time without facing any repercussions. Each participant provided signed consent forms as evidence of their informed consent (see Appendix C). The fact that the records would be kept for five years for publication purposes before being permanently destroyed was disclosed to the participants. The study's contribution to the body of knowledge would benefit South African public healthcare, it was also explained to the participants.

4.11 CHAPTER SUMMARY

In relation to the conclusions presented in this chapter confirm the research's positivist and inductive nature because the empirical model was constructed based on survey as well as the reviewed literature. A quantitative research method based on a positivist epistemology was used to address the research issues in Section 1.4. In addition, the information presented in this chapter supports the positivist and inductive nature of the research. Development of the study's instruments and an explanation of the measuring scales were discussed in this chapter. This chapter also covered the study population as well as the sample selection. Further, the rationale for the data gathering instruments and data analysis techniques used for this inquiry are presented and discussed in this chapter. In addition, the concepts of validity, dependability, and the data gathering tool were discussed. The chapter also discussed techniques for gathering and evaluating data. SPSS (Version 23.0) was employed to evaluate the data that was gathered.

CHAPTER 5: DATA ANALYSIS AND RESULTS

5.1 INTRODUCTION

The fourth chapter of this research provided an overview of the methodology and procedures used to organise and contextualise the research, as well as the tools used in data collecting, analysis, and presentation. This chapter summarises the findings of the data analysis, which were gathered using self-administered questionnaire. In order to extract insights from the data, this study used *SPSS (Version 23.0)* and AMOS software. Findings of this study are provided in the form of figures and tables, with explanations to make the study understandable, based on the empirical analysis as well as the results from prior studies.

This chapter is divided into sections and reports on the results of the quantitative approach. The survey respondents are covered in detail in the first section. Descriptive statistics and justifications for the data in the tables are provided in the second section. In the fourth section the findings of reliability testing using Cronbach's alpha are shown, and the results of exploratory factor analysis (EFA) are presented, and construct validity and how structural equation modelling (SEM) was used to test the research hypotheses are discussed extensively in the next. The findings of the investigation are summarised in the concluding section.

5.2 DATA PREPARATION

Data screening is the first step in the analysis of structural equation models (Schumacker & Lomax, 2016). A preliminary data processing process was carried out after the gathering of primary data from the study survey. Kumar (2016) recommends using a method for checking raw data for errors, omissions, and duplications. To improve the accuracy and quality of data entries, Kumar (2016) emphasises the need of data preparation prior to data analysis. The SurveyGizmo platform was used to export the survey data for this research study to a Microsoft Excel spreadsheet file. For accuracy and consistency, the data was double-checked (Zhang, Zhang, & Yang, 2016). In order to compute the mean and standard deviation values and to check for outliers, *SPSS*

(Version 23.0) was used to analyse the different data fields (van Zyl, 2014). The demographics of the participants are examined in the next section.

5.3 DESCRIPTIVE STATISTICS

Descriptive statistics is the term given to the analysis of data that helps describe, show, or summarise data in a meaningful way such that, for example, patterns might emerge from the data (Laerd Statistics, 2013). The following sections describe some of the statistics in this research study.

5.3.1 Demographics

The first section of the survey, known as the demographics section, was intended to gather background data on the participants in accordance with the design of the survey instrument. Participants had to answer questions on their gender, number of years of employment, and current position. In Table 5.1, the frequency distribution is summarised.

Table 5.1: Gender distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Gender	Female	169	61.9	62.1	62.1
	Male	104	38.1	37.9	100.0
	Total	300	100	100	

Table 5.1 shows that females accounted for (n = 169, 61.9%) of the total, while males accounted for (n = 104, 38.1%). This shows that the viewpoints of both genders of the participants in the study were represented in the sampling population. Overall, the gender mix of the studied population appeared to be balanced, and it reflected national demographic characteristics of the healthcare professional population.

Table 5.2: Age distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Age	Less than 25 years	26	9.5	9.5	9.5
	25-30 years	98	35.9	35.9	45.4
	31-40 years	102	37.4	37.4	82.8
	41- 50 years	23	8.4	8.4	91.2
	More than 50 years	24	8.8	8.8	100
	Total	300	100	100	

According to the data in Table 5.2, (n = 102, 37.4%) were between the ages of 31 and 40 years; (n = 98, 35.9%) were between the ages of 25 and 30 years; and (n = 26, 9.5%) were between the ages of less than 25 years. (n = 24, 8.8%) of the participants were over the age of 50, while (n = 23, 8.4%) of the participants were between the ages of 41 and 50. The results suggest that most of the respondents were of mature age and were expected to be truthful in their responses to the questionnaire.

Table 5.3: Work experience distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Work Experience:	Less than 1 year	19	6.3	6.3	6.3
	1-5 years	46	15.3	15.3	21.6
	6 – 10 years	132	44.0	44.0	65.6
	More than 10 years	103	34.3	34.4	100
	Total	300	100.0	100	100

Table 5.3 reveals that (n = 132, 44.4%) of the participants had 6 to 10 years of experience, (n = 103, 34.3%) had more than 10 years of experience, (n = 46, 15.3%) had less than 1 year of experience, and just (n = 19, 6.3%) had less than 1 year of experience. Many healthcare professionals in this survey had worked in the health sector for 6 to 10 years, according to the data. This suggests that, based on their years of experience, of the participants were knowledgeable in answering the survey questions.

Table 5.4: Position distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Position:	Medical doctor	12	4.0	4.0	4.0
	Pharmacist	8	2.7	2.7	6.7
	Gynaecologist	3	1.0	1.0	7.7
	Urologist	1	0.3	0.3	8.0
	Radiology	8	2.7	2.7	10.7
	Physiotherapist	8	2.7	2.7	13.4
	Nurse	225	75.0	75.0	88.4
	Dentist	8	2.7	2.7	91.1
	Others	27	9.0	7.9	100.0
	Total	300	100.0	100	100

Table 5.4 depicts the functionary responsibilities that the study's respondents perform daily. The data show that (n = 225, 75.0%) of the respondents were nurses, making them the most well-represented group. Medical doctors accounted for (n = 12, 4.0%), whereas pharmacists, radiologists, physiotherapists, and dentists each accounted for (n = 8, 0.8%). Gynaecologists were represented by (n = 3, 1.0%), urologists by (n = 1, 0.3%) and others by (n = 27, 9.0%). Nurses form most of the participants, given that the sampling technique was convenient sampling, this kind of results should be expected.

Table 5.5: Educational qualifications distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Qualification:	High School Certificate	1	0.4	0.4	0.4
	Diploma	68	24.9	24.9	25.3
	Bachelor’s Degree	175	64.1	64.1	89.4
	MBCHB	11	4.0	4.0	93.4
	Master’s Degree	17	6.2	6.2	99.6
	Doctorate (PhD)	1	0.4	0.4	100.0
	Total	300	100	100	100

Table 5.5 shows that (n = 175, 64.1%) had a bachelor's degree, (n = 68, 24.9%) had a diploma, and (n = 107, 6.2%) had a master's degree. (n = 11, 4.0%) have an MBCHB,

compared to (n = 1, 0.4%) who have a high school diploma and (n = 1,0.4%), (n = 1, 0.4%) had a doctorate. This suggests that majority of the respondents were intellectual and well-informed enough to comprehend and contribute to this study.

Table 5.6: Department affiliation distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Functional department:	Pharmacy	3	1.0	1.0	1.0
	Diagnostic Radiology and Imaging	5	1.7	1.7	2.7
	Intensive Care Unit	15	5.0	5.0	7.7
	General Surgery	20	6.7	6.7	14.4
	Causality	25	8.3	8.3	22.7
	Family Medicine	10	3.3	3.3	26.0
	Neonatal	15	5.0	5.0	31.0
	Gynaecology	10	3.3	3.3	34.3
	Urology	25	8.3	8.3	42.6
	Neurology	10	3.3	3.3	45.9
	Paediatric Surgery	20	6.7	6.7	52.6
	Paediatrics	27	9.0	9.0	61.6
	Physiotherapy	6	2.0	2.0	63.6
	Dentist	9	3.0	3.0	66.6
	Other	100	33.3	33.3	100
	Total	300	100.0	100.0	100

According to Table 5.6, the respondents work in a range of departments. It can be seen that the majority of participants were from other, accounting for (n = 100, 33.3%), followed by paediatrics (n = 27, 9.0%), causality and urology (n = 25, 8.3%), general surgery (n = 20, 6.7%), and paediatric surgery (n = 20, 6.7%), in that order. Family Medicine, Gynaecology, and Neurology with (n = 10, 3.3%) of the respondents working in each of those three departments, Neonatal and Intensive Care Unit each had (n = 15, 5.0%). However, (n = 9, 3.1%) were from the dentistry department, (n = 6, 2.0%) from physiotherapy, (n = 5, 1.7%) were from diagnostic radiology and imaging, and (n = 3, 1.0%) from the pharmacy department. The results show a balanced view of perspectives because of the empirical evidence provided in this research study.

5.3.2 **Use of Information Systems**

Respondents were asked to rate (1-3) statements using the scale provided: 1= No, 2=Yes, 3=Not Sure, (n = 58, 19.3%) responded with a (No), (n = 134, 44.7%) responded with a (Yes), and (n = 98, 32.8%)] (Not Sure). It is self-evident, however, that information systems exist, even if they are incomplete or uncertain. The frequency distribution is summarised in Table 5.7.

Table 5.7: Information systems availability distribution in hospital

Does your hospital have information systems (IS)?	Frequency	Percentage (%)
No	58	19.3%
Yes	134	44.7%
Not sure	98	32.8%
Total	300	100

Respondents were asked to rate (1-4) statements using the scale provided: 1= Extremely Important, 2=Very Important, 3= Important, and 4= Not Important in the corresponding spaces provided to evaluate: information systems availability distribution in hospital. (n = 91, 30.3%) thought it was important, (n = 84, 28.0%) thought it was very important, (n = 63, 21.0%) thought it was insignificant, and (n = 62, 20.7%) thought it was extremely essential. Based on their comments, it can be concluded that most of the respondents were aware of the importance of information systems. Table 5.8 summarises the frequency distribution.

Table 5.8: The degree of importance of information systems distribution of participants

		Frequency	Percent	Valid Percent	Cumulative Percent
Information systems use:	Not important	63	21.0	21.0	21.0
	Important	91	30.3	30.3	51.3
	Very Important	84	28.0	28.0	79.3
	Extremely important	62	20.7	20.7	100
	Total	300	100	100	100

On the list supplied in the questionnaire, respondents were also asked which functions should be included in the EHR. The pharmacy task was selected by (n = 98, 32.7%) of the participants, followed by the laboratory task by (n = 82, 27.3%). Nursing task by (n = 72, 24.0%) and patient admissions task by (n = 48, 16.0). Based on the findings of this study, healthcare professionals can be certain that if the needed capabilities are included in the EHR, it will provide them with accurate patient data. The frequency distribution is summarized in Table 5.9.

Table 5.9: Proposed EHR functions as suggested with participants

		Frequency	Percent	Valid Percent	Cumulative Percent
EMR functions:	Nurse tasks	72	24.0	24.0	24.0
	Patient admission task	48	16.0	16.0	40.0
	Laboratory task	82	27.3	27.3	67.3
	Pharmacy task	98	32.7	32.7	100
	Total	300	100	100.0	100

The variables' reliability was tested using *SPSS (Version 23.0).* Item analysis was performed on the three measurement instruments used in the study, and the results are presented in the following section.

5.4 CONSTRUCT ITEM'S RELIABILITY MEASURES

Altering existing scale components to create a new scale is a common strategy used in the development and validation of psychometric scales (Bodroža & Jovanović, 2016; Jenkins-Guarnieri, Wright & Johnson, 2013; Sigerson & Cheng, 2019). There are still more validation concerns to resolve, like making sure a stable scale is utilised as the basis for future study (Sigerson & Cheng, 2018). Internal consistency was examined in this study using Cronbach's alpha dependability, the most popular reliability indicator in social and organisational science (Bonett & Wright, 2015).

According to Malhotra (2019), an instrument's consistency throughout numerous measurements is referred to as reliability. Item consistency, or how closely a group of items (variables) measure the same thing, is known as item reliability. Such variables can be eliminated to improve the construct's dependability when the item's Cronbach's alpha value surpasses the construct's overall value. Thus, the corrected item-total correlation shows the association between the variable and the overall reliability of the other items in the questionnaire. There is no association between the overall scale and items with a corrected-item correlation of less than 0.4 (Field, 2016).

5.4.1 Electronic Health Records Construct Item Measures

Table 5.10: Item-total statistics (Electronic Health Records) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
EHR1	13.66	2.431	0.379	0.761	0.743	4
EHR3	13.26	1.931	0.568	0.665		
EHR4	13.15	1.838	0.697	0.590		
EHR5	13.23	1.919	0.521	0.696		

Cronbach's alpha index for the electronic health records (EHR) construct was found to be 0.743. The corrected item-total statistics for the measurement items under this construct are shown in Table 5.10. Measuring items EHR2 and EHR6 had a corrected item-total correlation of less than 0.1, which was deemed unacceptable. If these components were eliminated, the Cronbach's alpha coefficient of this construct would increase to 0.743 from 0.682, hence the construct items were removed.

5.4.2 Medical Error Reduction Construct Item Measures

The results of the reliability investigation for the medical error reduction (MER) construct are shown in Table 5.11. Cronbach's alpha coefficient for this construct was found to be 0.736. This shows a far higher level of internal consistency than the acceptable 0.7 (Hair, Black, Babin & Anderson, 2019). MER4, MER5 and MER6 construct item scores were shown to be non-correlated with other variables. If this item were eliminated, the Cronbach's alpha would improve from 0.701 to 0.736, hence the construct items were removed.

Table 5.11: Item-total statistics (Medical Errors Reduction) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
MER1	8.28	1.699	0.521	0.598	0.736	3
MER2	8.01	1.739	0.636	0.425		

MER3	7.78	2.578	0.405			

5.4.3 Diagnosis and Treatment of Diseases Construct Item Measures

The overall Cronbach's alpha coefficient for the construct diagnosis and treatment of diseases (DTD) was found to be 0.803. Table 5.12 shows the corrected item-total statistics for the measurement items for this construct. Measuring items DTD4, DTD5 and DTD6 had a corrected item-total correlation of less than 0.1, which was deemed unacceptable. If these components were eliminated, the Cronbach's alpha coefficient of this construct would increase to from 0.800 to 0.803, hence the construct items were removed.

Table 5.12: Item-total statistics (Diagnosis and Treatment of Diseases) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
DTD1	8.29	1.750	0.322	0.560	0.803	3
DTD2	8.15	1.214	0.445	0.358		
DTD3	8.23	1.072	0.405	0.443		

5.4.4 Better Coordination of Patient Care Construct Item Measures

The construct of improved patient care coordination (BCP) has an overall reliability of 0.763. Furthermore, the BCP5 and BCP6 measuring items had a corrected item-total correlation of less than 0.1, which was deemed inadequate. If these items were removed, the Cronbach's alpha coefficient for this construct would increase from 0.759 to 0.763 as indicated in the Table 5.13. For this reason, the construct items were removed.

Table 5.13: Item-total statistics (Better Coordination of Patient Care) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
BCP1	12.62	2.142	0.423	0.496	0.763	4
BCP2	12.46	1.935	0.374	0.524		
BCP3	12.63	2.093	0.434	0.486		
BCP4	12.47	1.889	0.307			

5.4.5 Information Quality Construct Item Measures

Table 5.14: Item-total statistics (Information Quality) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
IQ3	7.85	3.294	0.637	0.725	0.796	3
IQ4	7.96	3.530	0.701	0.671		
IQ5	8.02	3.170	0.597	0.776		

The results of the reliability investigation for the information quality (IQ) construct are shown in Table 5.14. Cronbach's alpha coefficient for this construct was found to be 0.796. This shows a far higher level of internal consistency than the acceptable 0.7 (Hair et al., 2019). IQ1, IQ2 and IQ6 construct item scores were shown to be non-correlated with other variables. If this item were eliminated, the Cronbach's alpha would improve to 0.796, hence the construct items were removed.

5.4.6 Knowledge Quality Construct Item Measures

Table 5.15: Item-total statistics (Knowledge Quality) construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
KQ2	12.86	2.096	0.460	0.456	0.887	3
KQ3	12.63	2.628	0.345	0.551		
KQ4	12.81	2.475	0.306	0.580		

The overall Cronbach's alpha coefficient for the construct knowledge quality (KQ) was found to be 0.887. The corrected item-total statistics for the measurement items under this construct are shown in Table 5.15. Measuring items KQ1, KQ5 and KQ6 had a corrected item-total correlation of less than 0.1, which was deemed unacceptable. If these components were eliminated, the Cronbach's alpha coefficient of this construct would increase to 0.897 and 0.830, hence the construct items were removed.

5.4.7 Service Quality Construct Item Measures

Table 5.16: Item-total statistics (Service Quality) construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
SQ1	8.32	1.353	0.456	0.114	0.461	3
SQ2	7.83	1.650	0.205	0.486		
SQ3	8.58	1.071	0.249	0.490		

The results of the reliability investigation for the service quality (SQ) construct are shown in Table 5.16. Cronbach's alpha coefficient for this construct was found to be 0.897. This shows a far higher level of internal consistency than the acceptable 0.7 (Hair et al., 2019).

SQ4, SQ5 and SQ6 item scores were shown to be non-correlated with other variables. If this item were eliminated, the Cronbach's alpha would improve to 0.897 from 0.805, hence the construct items were removed.

5.4.8 Perceived Usefulness Construct Item Measures

Table 5.17: Item-total statistics (Perceived Usefulness) construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
PU1	12.37	2.581	0.346	0.488	0.845	4
PU2	12.18	1.760	0.359	0.468		
PU3	12.23	2.307	0.408	0.431		
PU4	12.29	2.086	0.291	0.521		

The overall Cronbach's alpha coefficient for the construct usefulness (PU) was found to be 0.845. Table 5.17 shows the corrected item-total statistics for the measurement items under this construct. Measuring items PU5 and PU6 had a corrected item-total correlation of less than 0.1, which was deemed unacceptable. If these components were eliminated, the Cronbach's alpha coefficient of this construct would increase to 0.845 from 0.780, hence the construct items were removed.

5.4.9 Perceived Ease of Use Construct Item Measures

The reliability analysis for the construct perceived ease of use is shown in Table 5.18. (PEU). Cronbach's alpha coefficient for this construct was found to be 0.897. This shows a far higher level of internal consistency than the acceptable 0.7 (Hair et al., 2019). PEU4, PEU5, and PEU6 item scores were found to have non-correlation with other variables. If this item were eliminated, the Cronbach's alpha would increase to 0.897 from 0.753, hence these construct items were removed.

Table 5.18: Item-total statistics (Perceived Ease of Use) construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
PEU1	7.68	3.135	0.745	0.819	0.897	3
PEU2	7.63	3.096	0.742	0.821		
PEU3	7.73	2.935	0.761	0.805		

5.4.10 Technical Context Construct Item Measures

The overall Cronbach's alpha coefficient for the construct technical context (TC) was found to be 0.887. Table 5.19 shows the corrected item-total statistics for the measurement items under this construct. Corrected item-total correlations for the TC1, TC2, TC3 and TC6 measurement items were less than the allowed level of 0.1. If these components were deleted, the Cronbach's alpha coefficient of this construct would increase to 0.887 and 0.763, if these construct items were removed. For this reason, the construct items were removed.

Table 5.19: Item-total statistics (Technical Context) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
TC4	4.29	0.461	0.311		0.887	2
TC5	4.35	0.470	0.311			

5.4.11 Organisational Context Construct Item Measures

Table 5.20: Item-total statistics (Organisational Context) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
OC1	12.28	3.140	0.399	0.530	0.833	4
OC2	12.26	2.690	0.435	0.498		
OC3	12.04	3.189	0.425	0.515		
OC4	12.13	3.072	0.309	0.600		

The construct organisational context (OC) has a Cronbach's alpha rating of 0.833, which is considered good (Kline, 2016). This means that all the measurement items correspond to the same latent construct. Table 5.20 shows the item-total statistics for the observed items under this construct. The measurement items' Cronbach's alpha value was higher than the acceptable reliability criterion. As a result, these elements are thought to be measuring the same construct. Table 5.20 shows that eliminating any of the components has no influence on the alpha coefficient of the construct. However, for items OC5, was non-corrected item-total correlation was less than the requirement of 0.4.

5.4.12 Environmental Context Construct Item Measures

Table 5.21: Item-total statistics (Environmental Context) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
EC4	8.64	1.098	0.187	0.475	0.887	3
EC5	8.75	0.699	0.460	0.685		
EC6	8.72	1.074	0.182	0.487		

The overall Cronbach's alpha coefficient for the construct environmental context (EC) was found to be 0.887. The corrected item-total statistics for the measurement items under this construct are shown in Table 5.21. Measuring items EC1, EC2 and EC3 had a corrected item-total correlation of less than 0.1, which was deemed inadequate. If these constructs items were deleted, the Cronbach's alpha coefficient of this construct would increase to 0.887 from 0.712. For this reason, these items have been identified as being unsatisfactory, hence they were removed.

5.4.13 Evidence-Based Healthcare Practice Construct Item Measures

Table 5.22: Item-total statistics (Evidence-Based Healthcare Practice) Construct

Item-Total Statistics						
	Scale Mean if Item Deleted	**Scale Variance if Item Deleted**	**Corrected Item-Total Correlation**	**Cronbach's Alpha if Item Deleted**	**Cronbach's Alpha**	**N of Items**
EBHP1	12.40	2.878	0.486	0.613	0.782	4
EBHP2	12.41	2.471	0.457	0.624		
EBHP3	12.38	2.471	0.548	0.561		
EBHP4	12.41	2.605	0.395	0.667		

The reliability study for the construct evidence-based healthcare practice (EBHP) is shown in Table 5.18. Cronbach's alpha coefficient for this construct was found to be 0.782. However, the corrected item-total correlation for EBHP5 and EBHP6 was less than 0.1, hence these construct items were removed.

The next section discusses the measuring model for each latent and observable variable in the research model. Latent variables are concepts that cannot be directly assessed but are frequently used to explain observed behavioral variation (DeVault, 2016). Although latent variables cannot be seen directly, their relationship to visible variables can be assessed indirectly (Fornell & Larcker, 1981). The model is evaluated using exploratory factor analysis (EFA), confirmatory factor analysis (CFA), structural equation modelling (SEM) was used to evaluate the model.

5.5 EXPLORATORY FACTOR ANALYSIS

The exploratory factor analysis (EFA) method was used in this study to verify data validity. As noted in Chapter 4, the statistical technique adopted for the present is strong in determining the correct number of common components required to explain interactions between observable variables without imposing a pre-conceived framework on the results. EFA is also essential when it comes to developing underlying constructs for a group of measurable variables. Another way to see if the data is acceptable for factor analysis is to look at the intensity of inter-correlations between the variables.

According to Field, (2016), Hair et al. (2019) the main goal of factor analysis is to compress the information contained in a large number of original variables into a smaller number of new composite dimensions or variables (factors) with the least degree of information loss possible. *SPSS (Version 23.0) was* used to analysis EFA. Sample size, data screening, the strength of the correlations between the variables (Kaiser-Meyer-Olkin (KMO) measure), interpretation correlation, factor extraction, factor rotation, and factor analysis are all criteria to consider when deciding the appropriateness of the data. Furthermore, the Kaiser-Meyer-Olkin test, Bartlet's sphericity test, and communalities tests were used, and the results are reported in the section below.

5.5.1 Kaiser-Meyer-Olkin Measure of Sampling Adequacy

To evaluate whether the distribution of values was correctly sampled for factor analysis, the Kaiser-Meyer-Olkin (KMO) sampling adequacy test was utilized. The Kaiser-Meyer-Olkin (KMO) test is used to see if the value distribution of a dataset is suitable for factor analysis. This statistic has a range of 0 to 1, (0-1), with values closer to 1 and higher than 0.60 being acceptable (Hair et al., 2019). According to Field (2013), in order to do an adequate factor analysis, the KMO must be equal to or greater than 0.50. For this resaon, a KMO score of 0.50 or above was acceptable in this study. In this study, the KMO value is 0.554, which is a good percentage for factor analysis (Pallant & Routledge, 2020). Tables 5.23 and 5.24 show the communalities, the Kaiser-Meyer-Olkin (KMO) value, and the results of Bartlett's sphericity test.

Table 5.23: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.554
Bartlett's Test of Sphericity	Approx. Chi-Square	1214.866
	Df	528
	Sig.	0.000

5.5.2 Communalities

The term "commonalities" refers to the relationship that exists between one original variable and all the other variables in the study (Hair, et al., 2019). The values range from 0 to 1, with 0 indicating no variation explained by the common variance factors and 1 indicating that the common components fully explain all variance. A low communality score (less than 0.32) also suggests that the variable does not mesh well with other variables and should be deleted. All the measures had factor loadings greater than 0.5, indicating that they were well loaded. However, the researcher needs to study a range of estimation procedures to discover which is the most appropriate. Table 5.24 shows the communalities for all 31 items which were appropriate for further analysis and EC construct was excluded.

Table 5.24: Extraction of communalities

Communalities			**Communalities**		
Initial	**Extraction**	**Construct Item**	**Initial**	**Extraction**	**Construct Item**
1.000	0,693	EHR1	1.000	0,567	KQ2
1.000	0,670	EHR5	1.000	0,702	KQ3
1.000	0,751	EHR3	1.000	0,533	KQ4
1.000	0,578	EHR4	1.000	0,777	PEU1
1.000	0,642	MER1	1.000	0,783	PEU2
1.000	0,690	MER2	1.000	0,795	PEU3
1.000	0,434	MER3	1.000	0,485	OC1
1.000	0,641	DTD1	1.000	0,486	OC2
1.000	0,612	DTD2	1.000	0,511	OC3
1.000	0,565	DTD3	1.000	0,588	OC4

Communalities			Communalities		
1.000	0,537	BCP1	1.000	0,562	EBHP1
1.000	0,524	BCP2	1.000	0,591	EBHP2
1.000	0,535	BCP3	1.000	0,624	EBHP3
1.000	0,450	BCP4	1.000	0,464	EBHP4
1.000	0,707	IQ3	1.000		
1.000	0,758	IQ4	1.000		
1.000	0,656	IQ5	1.000		

Extraction Method: Maximum Likelihood (MLA)

In addition, methods such as the Ordinary least squares method and maximum likelihood estimate are examples of this. It follows that, the maximum likelihood (ML) estimation also provides standard errors for the parameters. Thus, the most accurate method of estimation is regarded to be maximum likelihood (Field, 2016). This is because it allows the researcher to compute a variety of goodness of fit indices, build confidence intervals, and do statistical testing of factor correlation as well as factor loadings. For this reason, for this investigation, the ML estimation technique was adopted. Further down, the extraction technique is discussed in detail in the next section.

5.5.3 Maximum likelihood analysis

Exploratory factor analysis (EFA) was performed to examine the questionnaires using the Maximum Likelihood Analysis (MLA) technique and the Promax Rotation Method to evaluate distinctions across the constructs (PRM). Pallant and Routledge (2020) stated that the main purpose of using MLA is to reduce the components to a minimal number of composite variables by putting the data into the pattern matrix plug in in AMOS (v23.0) from SPSS (v23.0). EFA factor analysis was also used to uncover hidden dimensions or constructs that were not apparent from a direct analysis (Pallant & Routledge, 2020). The surveys were developed based the conceptual framework developed (see Figure 3.2), to investigate the critical success factors for the adoption of EBHP.

Based on the conceptual framework for grouping the components, nine categories were established based on the literature review. It was also critical to make sure that all the components were loaded into their appropriate categories and that their eigenvalues were reasonable enough to be used in the final analysis (Pallant & Routledge, 2020). Constructs including environmental context (EC), technological context (TC), organisational context (OC), perceived usefulness (PU), and service quality (SQ) were deleted because they had lower loadings and eigenvalues below 1.0. Table 5.25, which is an extract from the component matrix, shows the results of the total variance explained. The table also displays the loadings for each factor on each rotational component that forms categorization groups.

The results show nine factors with eigenvalues values greater than 1.0. A second investigation was conducted using the scree plot. Figure 5.1 depicts the results of the scree plot. However, the scree plot does not make it clear which elements should be maintained. Instead, there are a few broad rules to follow. Only those with eigenvalues greater than one are taken into account. In order of decreasing eigenvalues, the eigenvalues were displayed. Furthermore, the decision was made to extract 9 components based on the various criteria, as shown in Figure 5.1.

Table 5.25: Maximum likelihood analysis of critical success factors

Constructs	**Construct items**	**Rotated component matrix value**	**Total variance explained**	**Eigenvalues**
Electronic health records (EHR)	EHR1	0,627	8.075	5,421
	EHR3	0,786		
	EHR4	0,807		
	EHR5	0,675		
Medical error reduction (MER)	MER1	0,765	7,944	2,734
	MER2	0,786		
	MER3	0,548		
Diagnosis and treatment of diseases records (DTD)	DTD1	0,684	7,724	2,147
	DTD2	0,714		
	DTD3	0,477		
Better coordination patent care (BCP)	BCP1	0,663	7,684	1,977
	BCP2	0,574		
	BCP3	0,660		

Constructs	Construct items	Rotated component matrix value	Total variance explained	Eigenvalues
	BCP4	0,554		
Information quality (IQ)	IQ3	0,829	7,007	1,638
	IQ4	0,861		
	IQ5	0,783		
Knowledge quality (KQ)	KQ2	0,703	6,374	1,332
	KQ3	0,788		
	KQ4	0,497		
Perceived ease of use (PEU)	PEU1	0,874	6,231	1,314
	PEU2	0,880		
	PEU3	0,883		
Organisational context (OC)	OC1	0,600	4,991	1,180
	OC2	0,527		
	OC3	0,655		
	OC4	0,547		
Evidence-based healthcare practise (EBHP)	EBHP1	0,701	4,971	1,168
	EBHP2	0,726		
	EBHP3	0,735		
	EBHP4	0,534		
Extraction method: Maximum Likelihood. *Rotation method: Promax with Kaiser Normalisation.* Rotation converged: in 9 iterations.				

Pallant and Routledge (2020) suggested using the scree plot to determine the number of factors to retain in an exploratory factor analysis (EFA) or principal component analysis (PCA) This will be explained further in the following section.

5.5.4 Scree plot

According to Ford, MacCallum, and Tait (1986); Ledesma and Valero-Mora (1986), factor analysis results are based on how many items to retain before choosing a factor rotation (2007). The graphical results of the screen test outperform the requirement of eigenvalues greater than 1 (Ford, MacCallum, & Tait, 1986). When identifying common factors, it is more rational to investigate the scree plots of the eigenvalues using Catell's scree test, according to a subsequent study (Fabrigar, Wegener, MacCallum & Strahan, 1999; Pallant, 2011; Cattell, 1966). A scree plot, as shown in Figure 8, is a graphical representation that includes the visual evaluation of a graphical representation of the eigen values.

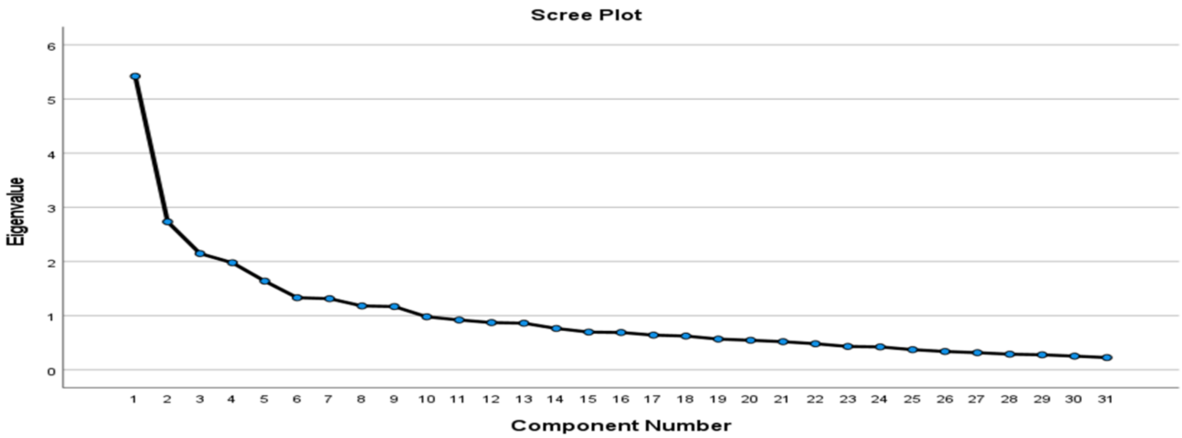


Figure 5.1: Scree Plot

Source: Author’s own research

In the screen test, the eigenvalues are presented in descending order and linked by a line. According to Ledesma and Valero-Mora (2007), a location where a drop or break has happened is identified. The scree plot in this thesis exhibits a clear break in the eigenvalue value trend after the seventh component. As shown in Figure 5.2, the graphical line for the screen plot drops until it encounters a break or bump in the curve. Hence, the point where it begins to straighten out is regarded to be an indication of the maximum number of factors where the eigenvalue cut off is more than 1.0 (Hair et al., 2019; Hair, Anderson, Tatham, & Black, 2020).

5.5.5 Interpretations of MLA results

According to Schreiber (2008), the rotation strategy aids in the detection of elements that load in each category. A factor is deemed loaded in a category if its loading value is greater than 0.3. (Pallant & Routledge, 2020). Table 5.25 shows that the first category retrieved (EHR factors) has the highest total variance explained. This indicates that the EHR explains the greatest amount of variation among the observable categories, meaning that it is strongly associated to several of them. When this statistic is applied to this study, it shows that the EHR is more important than the other elements. On the other hand, the second extracted category, MER, explains the most variation of the components not accounted for by EHR. This means that many of the elements that were less or not at all connected with the first group are correlated with this one. Similarly, this study shows that DTD variable has a significant impact on EBHP and several other constructs, such as KQ, BCP, IQ PEU, and OC, are independent of the dependent variable: EBHP.

According to the analysis, certain factors had split loadings, indicating that they loaded in more than one category as shown in Table 5.25. Furthermore, the exploratory factor analysis ignored the previously mentioned OC, EC, PEU and SQ. However, for this reason, their loading difference in their initial categories was too small (less than 0.3), and their modest loadings were deleted. In this study, the MLA of the 31 factors created, as well as the 9 extraction iterations, matched the nine categories identified in the literature reviewed. The initial 78 components were reduced to 31, accounting for (61.01%) of the total variation explained, with eigenvalues greater than 1. All the constructs which were reliable and valid using both Cronbach alpha and EFA were considered for further analysis in this study.

5.8 CORRELATION ANALYSIS

In this study the relationships between two or more variables in the model were examined. The study's aim was also to investigate if there is any primary evidence for the variables' relationships. Following that, the findings will be used to drive further study, such as regression analysis. Table 5.26 displays the correlations between each variable. Pearson's correlation coefficients (r) for the variables were significant at the 0.01 level. Correlation matrix in Table 5.26 shows a substantial positive relationship between the dependent and independent variables. BCP ($r=0.121$, $p< 0.05$), IQ ($r=.221$, $p <0.05$), KQ ($r=0.181$, $p< 0.05$), and DTD ($r=0.173$, $p <0.05$) are all significant and positively associated with EHR. However, the association between EBHP and DTD demonstrated a positive significant relationship ($r=0.299$, $p<0.05$). EBHP has a strong and positive relationship with BCP (r=0.294, p<0.05). Moreover, the data also showed that EBHP (r=0.122, p<0.05) has a substantial significant relationship with OC. BCP has a substantial and positive relationship with KQ (r=0.154, p<0.05). DTD (r=0.199, < 0.05) similarly these constructs have positive significance to MER.

PEU and EHR have a strong, significant positive relationship (r=0.158, p<0.05). Table 5.26 further shows that the correlations between the dependent and independent variables ranged from r=-.005 to r=.299, indicating that there were no issues with multicollinearity. Authors, Hair et al. (2019) do concur by stating that "an anlysis of the correlation matrix for the independent variables is the simplest and most obvious means of identifying collinearity, and the presence of high correlations (generally.90 and above) is the first indication of substantial collinearity." Arguably, the relationships between the other constructs such as (OC and EHR, EBHP and EHR, DTD and BCP, IQ and DTD, DTD and PEU, DTD and OC, DTD and KQ, BCP and IQ, BCP and PEU, BCP and OC, BCP and MER, IQ and PEU, IQ and OC, IQ and KQ, IQ and MER, PEU and OC, PEU and EBHP, PEU and KQ, PEU and MER, OC, and MER, EBHP KQ, EBHP and MER were insignificant.

Table 5.26: Inter-correlations among study variables

Correlations										
		EHR	**DTD**	**BCP**	**IQ**	**PEU**	**OC**	**EBHP**	**KQ**	**MER**
HER	Pearson Correlation	1	.173*	.121*	.221*	.158*	.070	.081	.181*	.081
	Sig. (2-tailed)		.029	0.045	.026	.035	.248	.181	.018	.181
	N	300	300	300	300	300	300	300	300	300
DTD	Pearson Correlation		1	-.005	.097	.052	.072	.299*	.099	.199*
	Sig. (2-tailed)			.931	.111	.392	.236	.003	.103	.023
	N		300	300	300	300	300	300	300	300
BCP	Pearson Correlation			1	-.107	.118	.012	.294*	.154*	.053
	Sig. (2-tailed)				.079	.052	.844	.004	.014	.095
	N				300	300	300	300	300	300

Correlations

		EHR	DTD	BCP	IQ	PEU	OC	EBHP	KQ	MER
IQ	Pearson Correlation				1	-.034	-.026	-.065	-.034	-.032
	Sig. (2-tailed)					.581	.672	.288	.268	.254*
	N				300	300	300	300	300	300
PEU	Pearson Correlation					1	.090	.045	.045	.081
	Sig. (2-tailed)						.138	.459	.459	.659
	N					300	300	300	300	300
OC	Pearson Correlation						1	.122*	.122*	.081
	Sig. (2-tailed)							.044	.044	.181
	N						300	300	300	300
EBHP	Pearson Correlation							1	.033	.022
	Sig. (2-tailed)								.166	.175
	N							300	300	300
KQ	Pearson Correlation								1	.181*
	Sig. (2-tailed)									.0032
	N								300	300
MER	Pearson Correlation									1
	Sig. (2-tailed)									
	N									300

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

EHR=Electronic health records, DTD=Diagnosis and treatment of diseases, BCP=Better coordination of patient care, MER=Medical error reduction, KQ=Knowledge quality, IQ=Information quality, PEU=Perceived ease of use, OC=Organisational context, EBHP=Evidence-based healthcare practice.

Only items well above the 0.7 threshold were selected for this study, according to the Cronbach's alpha in sections 5.4.1 to 5.4.13 of the thirteen construct items. This confirms and validates the EFA's reliability. The choice of oblique rotation during EFA was justified since it assumes a degree of correlation or interaction between the observed variables, which was confirmed. Therefore, EFA was regarded to be a success. During the CFA phase, the EFA results were used. Confirmatory factor analysis is further discussed in the next section.

5.9 CONFIRMATORY FACTOR ANALYSIS (CFA)

The second stage proves that discriminant validity is confirmatory factor analysis (CFA). Since CFA is concerned with the relationship between measured variables and their components, it is also referred to as the measurement model in SEM (Holmes-Smith, Coote & Cunningham, 2006). The CFA is used to assess how effectively the signs convey the idea (Hair et al., 2020). In structural equation modelling, a multivariate statistical technique is employed to determine if the measured variables accurately reflect the number of structures (Kline, 2016). Usually, the last step before running the structural equation model is confirmatory factor analysis (Brown, 2015). A statistical method called confirmatory factor analysis (CFA) is used to confirm the factor structure of a collection of observed data. Using CFA, it is possible to test the idea that there is a relationship between the variables that may be observed and the latent constructs that underpin them. The researcher postulates the relationship pattern a priori, employs theoretical knowledge, empirical study, or both, and then statistically tests the hypothesis.

Three hundred (300) medical healthcare professionals participated in the study and the sample size was higher than the minimum criterion. The developed model was underpinned by the updated DeLone and McLean's IS Success Model (DeLone & McLean, 2003), Technology Acceptance Model (TAM)] (Davis et al., 1989) as well as the Technology-Organisation-Environment framework (TOE) [(Tornatzky & Fleischer, 1990). For this reason, the model formulation is based on theoretical deduction rather than empirical observation. Convenience sampling was used to choose the study's participants. As a result, these assumptions were met. To see if the measurement model could explain the data variations, common goodness-of-fit indices (Kline, 2016) between the measurement model and the data was used.

Electronic health records (EHR), Diagnosis and treatment of diseases (DTD), Better coordination of patient care (BCP), Information quality (IQ), Knowledge quality (KQ), Medical error reduction (MER), Perceived ease of use (PEU), Organisational context

(OC), and Evidence-based healthcare practice (EBHP) were the nine variables in the initial CFA analysis model. EHR construct included four indicators EHR1, EHR3, EHR4 and EHR5, as well as BCP1-BCP4, OC1-OC4, and OC1-OC4, EBHP1-EBHP4. As indicated in Table 5.25, the PEU factor had only three indicators PEU1-PEU3, MER1-MER3, IQ3, IQ4 and IQ5, DTD1-DTD3, and KQ2-KQ4 each had three indicators. The measurement model for CFA using AMOS *(Version 23.0)* was investigated twice in this study, first in first order and then in second order.

Factor loadings (the strength of the association between the indicator variables and latent factors) should be at least 0.70, according to Fornell and Larcker (1981), and this is a major factor in deciding which indicator variables to retain in the final model. Factor loadings greater than 0.5 can also be considered (Johnson & Stevens, 2001). As the standardised factor loading of 0.5 and above is considered acceptable, this study used a cut-off value of 0.6 and above (Johnson & Stevens, 2001). Thus, to attain the best fit, the measurement model should also be checked and, if necessary, updated (Segars & Grover,1998). These can either be of the first order (measured directly by the indicator variables) or the second order (wherein first-order latent factors are connected to a single second-order component) (Byrne, 2016).

5.9.1 First-order CFA Model

The measurement model in this thesis was evaluated using maximum likelihood estimation methods. To evaluate how effectively a factor describes data, the CFA approach was used. This can be aided by looking at the model fit indices. In general, the model is regularly accepted if the fit indices are high. A model with weak fit indices will be updated until it achieves acceptable fit indices rather than being rejected. This study examined five fit indicators utilising the Pomykalski, Dion and Brock (2008) combination rule, Dion (2008), Cheung and Rensvold (2002). According to Hair, Anderson, Babin and Black (2014), Chi-squared statistics should be used alongside an absolute measure like RMSEA and an incremental index like CFI. The degree of freedom is used to calculate the AGFI fit index. However, sample size has an impact. Also, the value of the AGFI index rises along with the sample size. For AGFI a value between 0 and 1 acceptable. Values over 0.90 signify a good fit (Bayram, 2013). As a result, the following fit indices were employed in this study to evaluate model fit:

- Chi-square (χ^2), which also incorporates the degree of freedom (df) value and the overall (p-value), is one of the most fundamental absolute fit indices (Kline, 2016).
- The Comparative Fit Metric (CFI), which has values ranging from 0 to 1, is another widely used model fit index. Higher values denote a better fit. Values above 90 are usually linked to models that match data well (Byrne, 2016; Hair et al., 2019; Kline, 2016).
- The population's approximation error is taken into account via the root mean square error of approximation (RMSEA). Generally speaking, values below 0.05 indicate a good match, while values above 0.08 indicate acceptable population approximation flaws (Byrne, 2016).
- The goodness-of-fit index (GFI) for Maximum Likelihood estimation was developed by Jöreskog and Sörbom in 1990. A GFI that is nearer to 1 denotes a better fit. Values above 80 are usually linked to models that match data well (Byrne, 2016; Hair et al., 2018; Kline, 2016).
- The degrees of freedom accessible for model testing are considered by the adjusted goodness-of-fit index (AGFI). An AGFI greater than 0.9 indicates a favourable match (Holmes-Smith, 2011).
- Model comparison indices, often referred to as incremental indices, compare the fit of one baseline model to the fit of another model based on uncorrelated measurement data. All factor loading scores are set to 1 and all error values are set to 0. Examples of incremental indices include the Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), Normed Fit Index (NFI), and Non-Normed Fit Index (NNFI) (Schermelleh-Engel, Moosbrugger & Müller,2003; Kenny, Kaniskan & McCoach, 2014; Byrne, 2016).

Despite the fact that the measurement model has been validated using SPSS v 23.0 software, however, further analysis using EFA was advised by other studies (Byrne et al., 2007; Chen, Sousa & West, 2005; Cheung & Rensvold, 2002). As suggested by many researchers, modification indices were used as necessary to enhance model fit (Pomykalski, Dion & Brock, 2008; Rohani, Yusof & Mohamad, 2009). Following the model's rerun, AMOS *(Version 23.0)* produced an output of the ideal threshold without generating any additional error messages. Yu (2012) claims that numerous errors in the structural equation model can be avoided by limiting the regression weight parameter to one on each observable variable for each latent variable, as shown in Figure 5.2.

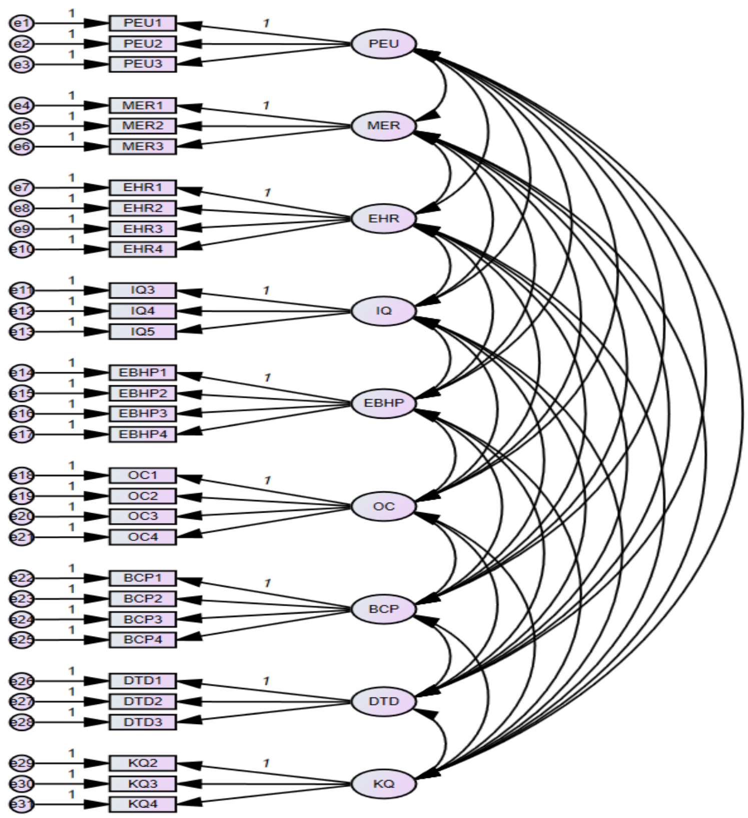


Figure 5.2: First-Run CFA Output Path Diagram

The model summary shows that CMIN/DF (2/d. f) = 1298. 859/465= 2.7932, which is within the range of the (χ^2/d. f) threshold of 2.1 to (χ^2/d.f) threshold of 3.1 (as shown in Table 5.27) indicating a relatively good fit. This ambiguity in fit model testing necessitates the evaluation of many fit models to remove the ambiguity (Cheung & Rensvold, 2002). (See Figure 5.2 and Table 5.27).

Table 5.27: Measurement Model (First Run)

Measurement Fit Indices	Conceptual Framework First Run	Measurement Fit Indices' Threshold Level	Acceptable/ Not Acceptable	Reference
χ^2	1298.859	Ratio 2.1 ≤ (X^2 /d. f) ≤ 3.1	Acceptable	Hallquist (2017)
d.f	465			
X^2 /d. f	2.793			
RMSEA	0.077	0.05≤ (RMSEA) ≤ 0.080	Acceptable	Kenny (2015)
CFI	0.998	≥ 0.950	Acceptable	Wang (2012)
TLI	0.899	≥ 0.90	Not Acceptable	Schumacker and Lomax (2018)
SRMR	0.0542	SRMR ≤ 0.08	Acceptable	Wang & Wang, 2012)

5.9.2 Second-order CFA Model

As already highlighted, the second form of CFA model, sometimes referred to as a hierarchical CFA model or second-order CFA model, has one or more shared direct causes for the lower-order latent variables that are tracked by the indicators (Byrne, 2016). Since the first-order factors are the lower-order factors and the common cause is measured by the lower-order latent factors, the common cause is sometimes referred to as a second-order factor (Byrne, 2016). The modification indices (MI) were reviewed in the second iteration to obtain the desired goodness-of-fit, in addition to looking for indicators of inferior loadings. There were no factors with inadequate loadings in this round of model fit. As a result, the emphasis was on employing modification indices to increase model fit. The process of the measurement model enhancement was further explained in the next section.

5.9.3 Modification of the Measurement Model

Model adjustment was required, as indicated by the fit indices CFI and GFI in Table 5.11. As Dion (2008) points out, without model adjustment, all fit indices measurements are unlikely to exhibit best fit. The refinement indices threshold is determined by specifying the level 2 change that must be incorporated in the output, with the default being 4.00 or near to 4.00. AMOS *(Version 23.0)* output was recomputed using the elimination strategies advised by Dion (2008) and Cheung and Rensvold (2002) to find the best fit.

Furthermore, all the standardised regression weights must exceed 0.5. (Preferably above 0.7). The 0.5 criteria must be met for all squared multiple correlations. Further the measurement errors of the items were also subjected to covariance restrictions to enhance model fit, after modification indices were examined.

In this study, the greatest modification indices are obtained in 13 pairs of residual covariance, according to Table 5.12. These should be eliminated or considered undefinable arguments. The results reveal that rerunning the measurement model with the covariance between e19 and e29 treated as a free parameter reduces model disagreement by at least 5.689. As a result, from its current value of 1298.851, the χ^2 statistics of measurement model will drop by 75.029 points. Only variables having a high correlation and high regression weights were removed from the analysis.

Table 5.28: Error Terms Covariance

Error terms			**Covariance**	**Error terms**			**Covariance**
e19	<-->	e29	5.689	e15	<-->	e19	5.697
e19	<-->	e25	7.518	e14	<-->	e23	4.046
e19	<-->	e21	8.135	e14	<-->	e18	8.250
e17	<-->	e21	6.183	e13	<-->	e21	4.329
e16	<-->	e25	5.702	e13	<-->	e17	5.659
e16	<-->	e21	4.258	e11	<-->	e25	6.611
e15	<-->	e24	7.281				

In this model, variables with no regression weight were not deleted; instead, they were treated as free parameters. As shown in Table 5.13, KQ2, BCP4, OC4, OC2, OC1, EBHP2, EBHP1, IQ3, EHR4 and PUE2 require modification indices and were treated as free parameters. When AMOS *(Version 23.0)* was run after addressing the modification indices (MI) covariance, all standardised regression weights and squared multiple correlations were above 0.5, and all standardised residual covariance were above 2.58 or below, 2.58. The improved model produced a new set of results that were significantly acceptable. As a result, the new results were calculated using 1118.859 chi-square statistics with 465 degrees of freedom (χ^2/d. f = 1118.859/465 = 2.4061). In relation to the revised output shows χ^2/d. f values that are close to the limits' lower bound, indicating a good fit. Confirmed fit indices also improved outputs, with all results indicating a satisfactory model fit. These results indicated that the model was well-fitting, with RMSEA = 0.045, CFI = 0.998, TLI = 0.901, and SRMR = 0.0542. (See Figure 5.3 and Table 5.30).

Table 5.29: Regression Weights between Constructs and Construct Items

Path	Regression weights	Path	Regression Weights
KQ2<-- OC	4.713	EBHP1<-- PEU	18.466
BCP4<-- EBHP	6.323	IQ3<-- OC	7.207
OC4<-- KQ	4.324	EHR4<-- BCP	6.664
OC2<-- EBHP	4.649	EHR4<-- PEU	5.273
OC1<-- BCP	10.699	EHR4<-- KQ	5.552
OC1<-- PEU	12.832	PEU2<-- EF3	4.131
EBHP2<-- MER	7.062	PEU2<-- KQ	5.674
EBHP1<-- BCP	15.416		

There are numerous fitness indices that show how well the model fits the data, (Awang (2014). According to Awang (2014), researchers are divided on the fitness indices to use, citing (Hair et al.,2020; Holmes-Smith, 2011). However, only one fitness indication from each model fit category should be used. The model fit indices for the structural model are listed in Table 5.53.

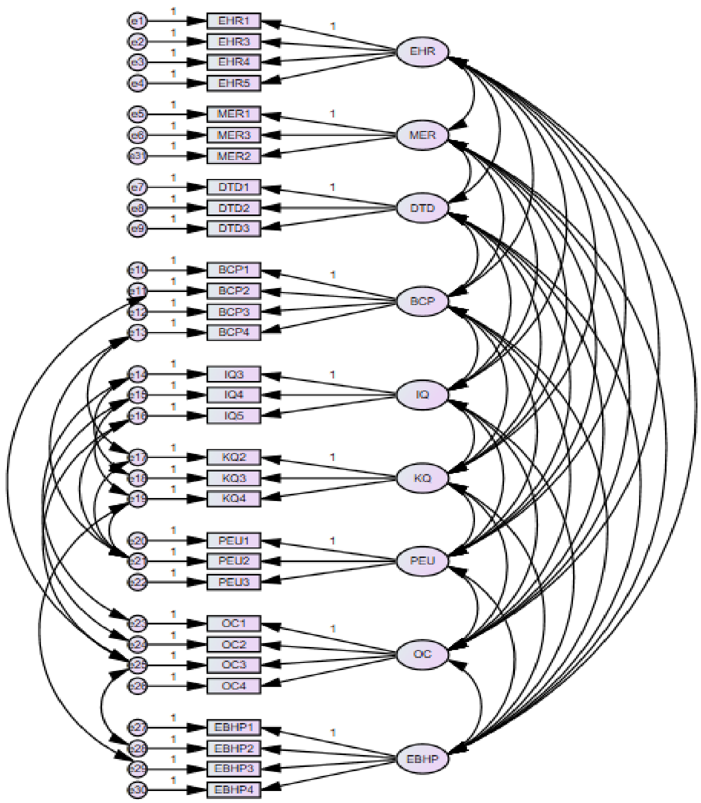


Figure 5.3: Second-Run CFA Output Path Diagram

In this phase, the researcher calculates the causal relationships between the primary construct and each of its subconstructs. Here, the goal was to calculate the factor loading of the main construct on its sub-constructs to verify that the second order construct loads into the corresponding sub-constructs as predicted. For each item, the CFA technique would also, as normal, estimate the factor loading. The values of the measurement model (Second Run) are shown in Table 5.30. All these indices have values between roughly 0 and 1.0, with a cut off score of around.95. The closer they go to 1, the better. CFI and TLI for this model, respectively was ≥ 0.950 and ≥ 0.90, which imply an acceptable overall model fit, in accordance with Figure 5.3. A result of.05 or below denotes an adequate model fit, while the Root mean square error of approximation (RMSEA), which runs from 0 to 1, is suggestive of a lesser value. The RMSEA for this model was ≤ 0.080 and the SMRM was ≤ 0.08, both of which support the CFI and TLI's good fit indices.

Table 5.30: Measurement Model (Second Run)

Measurement Fit Indices	Conceptual Framework Second-Run	Measurement Fit Indices' Threshold Level	Acceptable/ Not Acceptable	Reference
χ^2	1118.859	Ratio 2.1 ≤ (X^2 /d. f) ≤ 3.1	Acceptable	Hallquist (2017)
d.f	465			
X^2 /d. f	2.4061			
RMSEA	0.045	0.05≤ (RMSEA) ≤ 0.080	Acceptable	Kenny (2015)
CFI	0.978	≥ 0.950	Acceptable	Wang (2012)
TLI	0.901	≥ 0.90	Acceptable	Schumacker and Lomax (2018)
SRMR	0.0542	SRMR ≤ 0.08	Acceptable	Wang & Wang, 2012)

Table 5.31 shows (a) the item's standardised factor loading, (b) the item's r-squared value, which shows the percentage of item variance explained by the linked common factor, (c) the construct composite reliability (CCR), and (d) the average variance extracted (AVE).

Table 5.31: Results of Confirmatory Factor Analysis (CFA)

Construct	Indicator	Factor Loading	R^2	P-Value	CCR	AVE
Electronic health records (EHR)	EHR1	0.627	0.742	Not Significant	0.742	0.751
	EHR2	0.786				
	EHR3	0.807				
	EHR4	0.675				
Perceived Ease of Use (PEU)	PEU1	0.874	N/A	N/A	0.869	0.831
	PEU2	0.880				
	PEU3	0.883				
Medical Error Reduction (MER)	MER1	0.765	0.00	Not Significant	0.692	0.791
	MER2	0.786				
	MER3	0.543				
Information Quality (IQ)	IQ3	0.829	0.780	Significant	0.795	0.83

	IQ4	0.861				
	IQ5	0.783				
Evidence Based Health Practice (EBHP)	EBHP1	0.701	0.159	Significant	0.681	0.34
	EBHP2	0.726				
	EBHP3	0.735				
	EBHP4	0.534				
Organisational Context (OC)	OC1	0.600	N/A	N/A	0.606	0.885
	OC2	0.527				
	OC3	0.655				
	OC4	0.547				
Better Coordination of Patient Care (BCP)	BCP1	0.663	0.159	Significant	0.593	0.778
	BCP2	0.574				
	BCP3	0.660				
	BCP4	0.554				
Diagnosis and Treatment of Diseases (DTD)	DTD1	0.684	0.153	Significant	0.568	0.765
	DTD2	0.714				
	DTD3	0.477				
Knowledge Quality (KQ)	KQ2	0.703	0.023	Not Significant	0.596	0.754
	KQ3	0.588				
	KQ4	0.497				

A measure of convergent validity is the average variance explained (AVE). It expresses how much variance is captured by a construct vs how much variance is due to measurement error (Stralen, Yildirim & Velde, 2019). In general, an AVE score of >.50 suggests that the construct has high convergent validity. Table 5.31 shows that all four constructs (EBHP, BCP, IQ, EHR, DTD) in the fitted confirmatory factor analysis model had AVE values greater than the.50 cut off criterion. Given such results, it is safe to conclude that the constructs explained more of variance than the measurement error.

The construct composite reliability (CCR) is a composite reliability measure used in confirmatory factor analysis. It is a similar metric to Cronbach's alpha (α). While the construct composite reliability criteria are debatable, most technique literature recommend that construct composite reliability values greater than.70 indicate excellent composite reliability (Bandalos, 2018; Stralen, Yildirim & te Velde, 2019). It follows that the construct composite reliability for the four constructs ranged from.731 to.881 in the confirmatory factor analysis fitted model, which implies they were all above the recommended cut off of.70. These findings revealed that the usual convergent validity and composite reliability criteria had been met. As a result, the measurement model was found to be valid and trustworthy, and it was appropriate for use in structural equation modelling analysis.

5.10 MULTIPLE REGRESSION ANALYSIS

Moreover, the correlation technique was used to examine the eleven hypotheses of the current study in the previous section. To further examine the various hypotheses, this study used multiple regression technique. *SPSS (Version 23.0)* was used to run regression, which is an extension of basic correlation. The technique is also known as causal links modelling and is used to forecast the dependent variable using the independent variables (Pallant & Routledge, 2020). Multiple regression is used to analyze the constructs: electronic health records (EHR), information quality (IQ), knowledge quality (KQ), medical error reduction (MER), better coordination of patient care (BCP), service quality (SQ) and evidence-based healthcare practice (EBHP). Equally important the significant impact of these constructs on EBHP was also investigated.

5.10.1 Regression Analysis for Electronic Health Records (EHR)

Multiple regression analysis' residual errors are believed to be randomly distributed and unrelated to one another (Field, 2013). To make sure the residual terms were normal, the histogram and normal probability plots were made. Figure 5.4 depicts a histogram with normal curves for the regression model involving the dependent variable: EHR. In light of the literature review, the output demonstrates that the residuals are normal based on the symmetric bell curve form that is not skewed and is therefore centered around the mean (Tabaschnick & Fidell, 2019). The graph shows a normal residual distribution that satisfies the normality requirement.

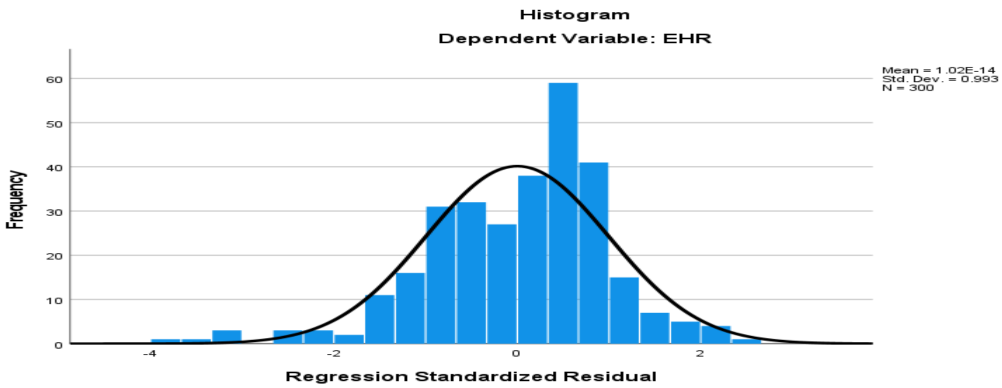


Figure 5.4: Histogram of standardised residuals for EHR with the normal curve

A typical P-P plot of the residuals from the regression model for electronic health records (EHR) is shown in Figure 5.16. The residuals are compared to the straight diagonal line of the normal distribution. According to Hair et al. (2018), the distribution is referred to as normal if the residual line is perpendicular to the diagonal. Osborne, Jason and Waters (2019) further noted that, since the residuals follow the diagonal with little variance, they in particular resemble a normal distribution.

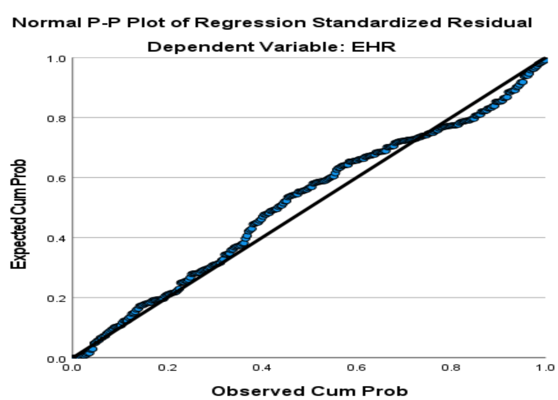


Figure 5.5: Normal P-P plot for the regression residual EHR

The model summary shown in Table 5.31 is the result of the initial regression model evaluation. According to the findings PEU was sufficient to account for the impact of EHR. This was confirmed by the coefficient of determination (R^2=0.119), which showed that changes in the impact of EHR accounted for (11.9%) of changes in PEU. Table 5.32

shows, the impact on PEU in relation to EHR. Regression analysis using ANOVA was used to validate the model.

Table 5.32: Model summary for the regression model – EHR

Model Summary										
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					
					Square Change	F Change	df1	df2	Sig. F Change	Durbin Watson
1	.345	0.119	0.107	0.42019	0.119	9.963	4	295	0.00	1.867
a. Predicators: (Constant), PEU										
b. Dependent Variable: EHR										

Table 5.33 showed that the model was statistically significant. The results also indicated that the impact of EHR was strongly predicted by PEU. Furthermore, this result was supported by a F (4.296=9.963, $p < 0.05$). Using a simple linear regression coefficient, the relationship between EHR and PEU was determined. Table 5.33 summarized the results.

Table 5.33: ANOVA for the regression model EHR

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	7.036	4	1.759	9.963	.000
	Residual	52.085	295	0.177		
	Total	59.121	296			
a. Dependent Variable: EHR						
b. Predictor: (Constant), PEU						

The standardized coefficients of the model depict the relative importance of each construct. Table 5.34 shows that PEU and EHR have a statistically significant relationship ($\beta = 0.209$, $t = 3.822$, $p<0.05$). These findings demonstrated a strong positive statistically significant relationship between the predictors, PEU and EHR.

Table 5.34: Coefficients of regression model - EHR

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	2.947	0.295		9.981	0.000	2.366	3.528		
	PEU	0.177	0.044	0.209	3.822	0.000	-0.056	0.058	0.977	1.024
	a. Dependable Valuable: EHR									

5.10.2 Regression Analysis for Better Coordination of Patient Care (BCP)

In some studies researchers have used hierarchical multiple regression to examine the potential moderating roles (You, 2015; Costanzo & Desimoni, 2017). IQ, KQ, and EHR will all be analysed in this study using hierarchical multiple regression. Table 4.41 represents the outcomes of the moderated regression analysis are displayed in Figure 5.14 shows the histogram of residuals in the regression model for the dependent variable: BCP. The residuals histogram was discovered to be reasonably normal and to be close to the normal curve.

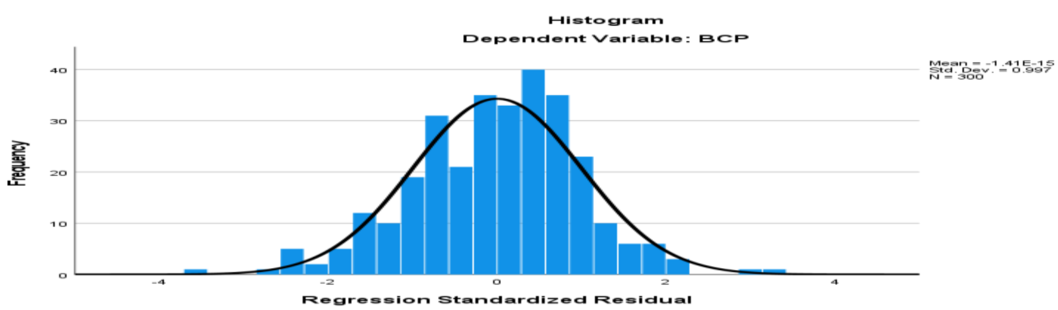


Figure 5.6: Histogram of standardised residuals for BCP

Figure 5.7 displays the P-P plot of the residual for the regression model with BCP. The normality assumption was confirmed because there were no significant deviations from normality in the residuals (Tabaschnick & Fidell, 2013).

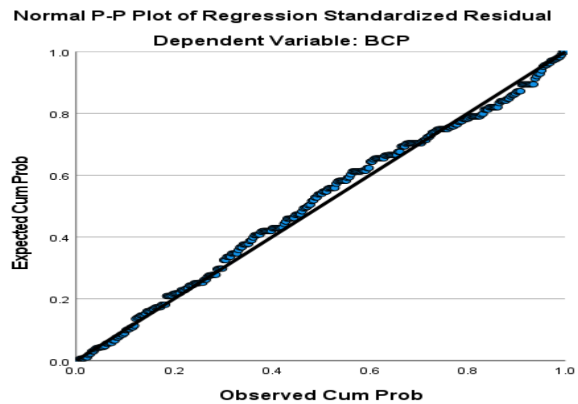


Figure 5.7: Normal P-P plot for the regression residual - BCP

This resulted in the R^2 change, which showed the increase in variance accounted for by the new interaction term. R^2 2 change increased by 0.159, indicating a (15.9%) increase in the amount of variation that the extra interaction term could explain. It is important to note that the increase in variation is statistically significant ($p<0.05$), indicating that EHR, KQ, IQ all significantly have significant positive influence on BCP. Table 5.35 outlines the results of the Analysis of Variance (ANOVA) for IQ, KQ and EHR as mediating variables of BCP.

Table 5.35: Model summary for the regression model - BCP

Model Summary										
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					
					R Square Change	F Change	df1	df2	Sig. F Change	Durbin Watson
1	.399	0.159	0.154	0.47074	0.159	28.055	2	295	0.00	2.119
a. Predicators: (Constant), IQ, KQ, EHR										
b. Dependent Variable: BCP										

The relationship between the constructs EHR, IQ, and KQ was statistically significant ($F (2.298) = 28.055$, $p <0.05$). Furthermore, it meant that the model was statistically significant and appropriate for further investigation. In addition, the association between BCP and EHR, IQ and KQ, as shown in Table 5.36, using ANOVA for regression analysis to identify the moderating effect of BCP.

Table 5.36: ANOVA for the regression model - BCP

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	12.434	2	6.217	28.055	.000
	Residual	65.594	298	0.222		
	Total	78.028	298			
a. Dependent Variable: BCP						
b. Predictors: (Constant), IQ, KQ, EHR						

Each construct's relative importance is represented by the model's standardised coefficients. The findings show that there is no statistically significant relationship between BCP and KQ (β = 0.043, t = 0.705, p < 0.05). BCP and IQ have a negative and statistically insignificant relationship, according to the predictor variables (β = -0.080, t = -1.320, p< 0.05). However, there was a statistically significant relationship between BCP and EHR (β= 0.125, t = 2.043, p <0.05). Overall, the results show a strong statistically significant correlation between the dependent variable BCP and the predictors IQ, KQ, and EHR.

Table 5.37: Coefficients of the regression mode- BCP

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	3.903	0.482		8.100	0.000	2.954	4.851		
	KQ	0.035	0.050	0.043	0.705	0.481	-0.064	0.135	0.976	1.024
	IQ	-0.061	0.046	-0.080	-1.320	0.188	-0.154	0.030	0.986	1.014
	EHR	0.136	0.066	0.125	2.043	0.042	-0.005	0.267	0.975	1.026
	a. Dependable Valuable: BCP, DTD									

5.10.3 Regression Analysis for Diagnosis and Treatment of Diseases (DTD)

It is assumed that residual errors in multiple regression are equally distributed and unrelated to one another (Field, 2013). The histogram and normal probability plots were produced to make sure the residual terms were normal. Figure 5.8 depicts a histogram with normal curves for the regression model for the dependent variable: DTD. According to Tabaschnick and Fidell (2019). Therefore, this defines the output which demonstrates that the residuals are normal due to the symmetric bell curve form that is not skewed and is therefore centered around the mean. It follows that the graph exhibits a normal residual distribution in accordance with the normality criteria.

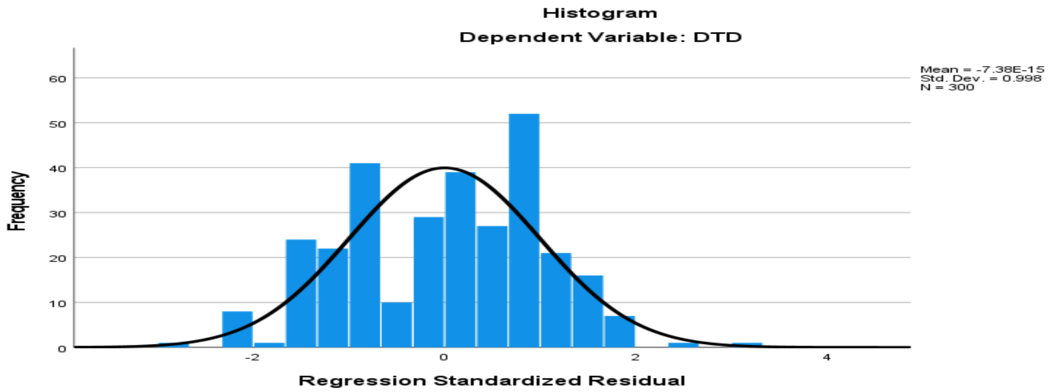


Figure 5.8: Histogram of standardised residuals for DTD with the normal curve

Figure 5.9 displays a typical P-P plot of the residuals for the regression model - diagnosis and treatment of diseases (DTD). The residuals are contrasted with the normal distribution's straight diagonal line. If the residual line is parallel to the diagonal, the distribution is said to be normal (Hair et al., 2018). As a result, the residuals follow the diagonal with the least amount of variance, giving the impression that they are distributed normally.

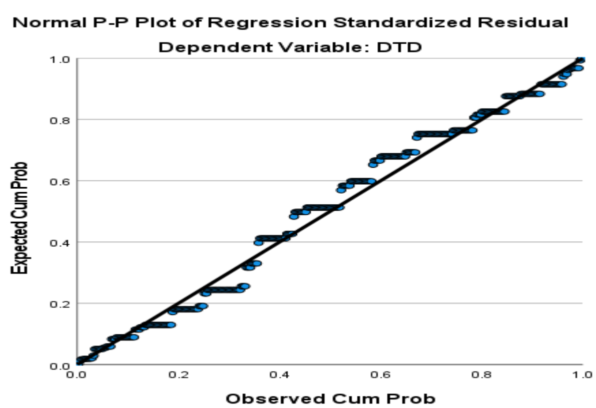


Figure 5.9: Normal P-P plot for the regression residual DTD

MER was found significant in explaining the construct disease diagnosis and treatment, as evidenced by the findings in Table 5.38. This was confirmed by the coefficient of determination (R^2=0.159), which suggested that the decrease in MER was responsible for (15.9%) of the overall changes in DTD. The remaining (84.1%) was explained by other factors. Table 5.38 shows the findings of Analysis of Variance (ANOVA) on MER as well as DTD.

Table 5.38: Model summary for the regression model - DTD

Model Summary										
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					
					R Square Change	F Change	df1	df2	Sig. F Change	Durbin Watson
1	.395	0.159	0.153	0.48407	0.159	55.098	1	298	0.000	2.007
a. Predicators: (Constant): MER										
b. Dependent Variable: DTD										

The results show that the model was statistically significant. Furthermore, it was concluded that medical error reduction (MER) was a good predictor of disease diagnosis and treatment (DTD). MER and DTD constructs were found to have a statistically significant relationship, as shown by F (2.298) = 55.098, ($p<0.05$). In addition, regression analysis using ANOVA was used to ascertain the moderating effect between MER and DTD are shown in Table 5.39.

Table 5.39: ANOVA for the regression model - DTD

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	12.911	1	12.911	55.098	.000
	Residual	69.830	298	0.234		
	Total	82.741	299			
a. Dependent Variable: DTD						
b. Predictors: (Constant): MER						

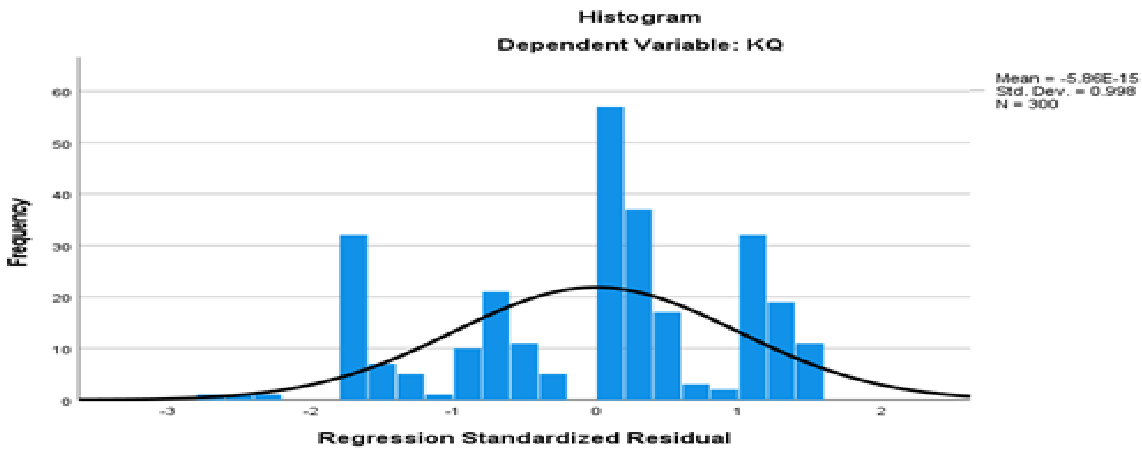
Table 5.40 displayed the standardized coefficients for the predictor variables. The standardized coefficient shows the weight of each construct in the model. EHR have a statistically significant influence on DTD (β= 0.054, t = 0.472, $p<0.05$). It follows that, the correlation between DTD and MER was found to be statistically insignificant (β = -0.010, t = -0.010, $p<0.05$). However, the results show that the relationship between the predictors: DTD and the dependent variable: MER is statistically significant in the positive direction.

Table 5.40: Coefficients of regression model - DTD

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	4.095	0.353		11.587	0.000	3.399	4.791		
	EHR	0.049	0.105	0.054	0.472	0.637	-0.157	0.256	0.285	3.507
	MER	-0.013	0.146	-0.010	-0.087	0.931	-0.300	0.274	0.285	3.507
	a. Dependable Valuable: DTD									

5.10.3 Regression Analysis for Knowledge Quality (KQ)

Hierarchical multiple regression was used to examine the moderating effects of medical



error reduction (MER) and electronic health records (EHR) on knowledge quality (KQ). Table 5.40 shows outcome of the moderated regression analysis. Similarly, Figure 5.10 displays the histogram of residuals in the regression model for the dependent variable: KQ. The residuals' histogram was discovered to be reasonably normal, suggesting that the residuals were normal. Figure 5.11 displays a P-P plot of the residual for the regression model with KQ. The residuals were found to be normal, with no discernible departures from normality, satisfying the assumption of normality (Tabaschnick & Fidell, 2013).

Figure 5.10: Histogram of standardised residuals for KQ

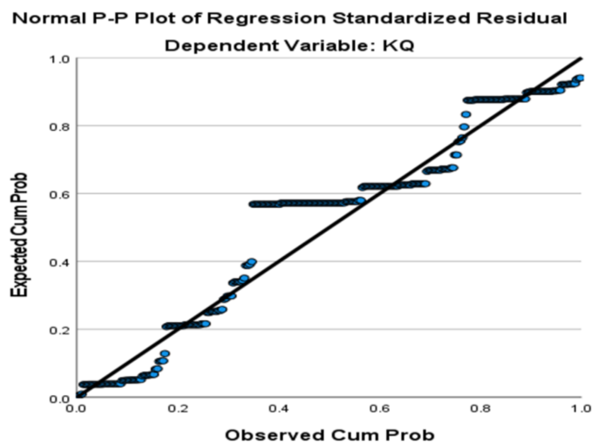


Figure 5.11: Normal P-P plot for the regression residual – KQ

This resulted in the R^2 change, which showed the increase in variance accounted for by the new interaction term. The new interaction term causes a change in R^2 of 0.151, which indicates an increase in variation of (15.1%). It is important to note that the increase in variation is statistically significant ($p<0.05$), indicating that EHR and MER have a favorable significant impact on KQ. Table 5.41 presents the findings of the Analysis of Variance (ANOVA) for MER and the moderating effect of EHR on KQ.

Table 5.41: Model summary for the regression model - KQ

Model Summary									
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					Square Change	F Change	df1	df2	Sig. F Change
1	.151	0.023	0.016	0.51239	0.023	3.148	2	298	0.045
a. Predicators: (Constant), MER, EHR									
b. Dependent Variable: KQ									

Table 5.42 includes an analysis of the model's fitness using the Analysis of Variance (ANOVA). A statistically significant relationship between the constructs of MER and EHR on KQ was found, as shown by F (2.298) = 3.148, ($p<0.05$). Furthermore, regression analysis using ANOVA was used to ascertain the moderating effect between MER as well as EHR on (KQ), as shown in Table 5.42.

Table 5.42: ANOVA for the regression model - KQ

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	1.653	2	0.826	3.148	.045
	Residual	70.886	298	0.263		
	Total	72.538	298			
a. Dependent Variable: KQ						
b. Predictors: (Constant), MER, EHR						

The results of the regression coefficients are displayed in Table 5.43. Each construct in the model is ranked according to importance using the standardized measure. KQ and EHR had a positive and statistically significant relationship (r = 0.137, t = 2.216, p<0.05). It was discovered that there is a statistically significant relationship between KQ and MER (β=0.016, t = 0.144, p<0.05). Table 5.3 shows a positive statistically significant association between the dependent variable, KQ and the two predictors, EHR and MER.

Table 5.43: Coefficients of the regression model - KQ

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta	T	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	3.364	0.502		6.707	0.000	2.376	4.351		
	EHR	0.181	0.149	0.137	2.216	0.025	-0.112	0.474	0.285	3.507
	MER	0.030	0.207	0.016	0.144	0.885	-0.377	0.437	0.285	3.507
	a. Dependable Valuable: KQ									

5.10.4 Regression Analysis for Information Quality (IQ)

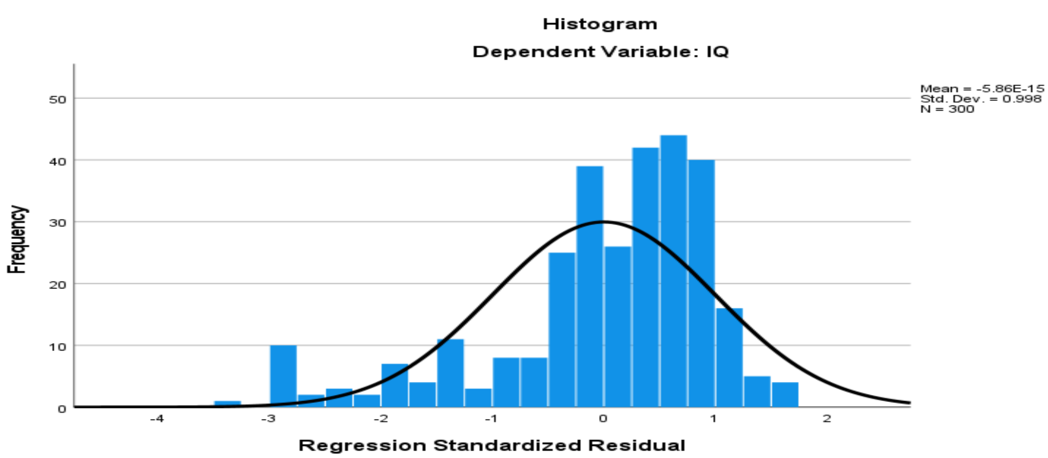


Figure 5.12: Histogram of standardised residuals for IQ with the normal curve

It is assumed that residual errors in multiple regression are equally distributed and unrelated to one another (Field, 2016). The histogram and normal probability plots were produced to make sure the residual terms were normal. A histogram with normal curves for the regression model for the dependent variable IQ is shown in Figure 5.12. Based on the symmetric bell curve form that is not skewed and is therefore centered around the mean, the output shows that the residuals are normal (Tabaschnick & Fidell, 2019). According to the normality assumptions, the graph displays a normal residual distribution. Figure 5.13 displays a typical P-P plot of the residuals for the regression model with IQ. The residuals are contrasted with the normal distribution's straight diagonal line. If the residual line is parallel to the diagonal, the distribution is said to be normal (Hair et al., 2019). Hence, the residuals follow the diagonal with the least amount of variance, giving the impression that they are distributed normally.

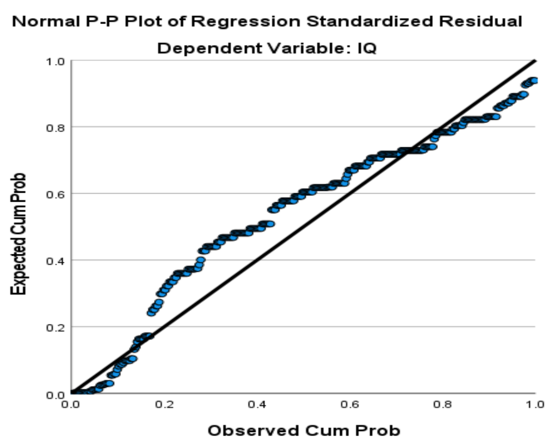


Figure 5.13: Normal P-P plot for the regression residual IQ

The model summary shown in Table 5.44 is the result of the initial regression model evaluation. According to the results, electronic health records (EHR) were deemed to be a satisfactory explanation for information quality (IQ). This was confirmed by the coefficient of determination (R^2 = 0.577), which showed that other factors accounted for (42.3%) of the model's total variation, leaving EHR to account for (57.7%) of it. in Table 5.44 shows the model for EHR and its impact on IQ were further validated using the results of Analysis of Variance (ANOVA).

Table 5.44: Model summary for the regression model - IQ

Model Summary										
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					
					Square Change	F Change	df1	df2	Sig. F Change	Durbin Watson
1	.76	0.517	0.577	0.64261	0.006	1.717	1	298	0.001	1.542
a. Predicators: (Constant), EHR										
b. Dependent Variable: IQ										

Table 5.45 includes an analysis of the model's fitness using the Analysis of Variance (ANOVA). A statistically significant relationship between the constructs of MER and EHR on KQ was found, as shown by F (1.299) = 1.717, ($p <0.05$). Thus, it was possible to draw the conclusion that the model accurately described the phenomenon under study and that each variable adequately explained its contribution towards the adoption of EBHP. To ascertain the moderating impact between EHR and IQ, regression analysis using ANOVA is shown in Table 5.45.

Table 5.45: ANOVA for the regression model IQ

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	0.709	1	0.709	1.717	.000
	Residual	123.059	298	0.413		
	Total	123.768	299			
a. Dependent Variable: IQ						
b. Predictors: (Constant), EHR						

Table 5.46 shows the results of the regression coefficients are displayed. Each construct in the model is ranked according to importance using the standardized measure. IQ and EHR showed a positive and statistically significant relationship (β= 0.276, t = 3.310, $p<0.05$). The results show that the dependent variable: IQ and the predictor: EHR statistically significant positive relationship.

Table 5.46: Coefficients of regression model - IQ

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta			Lower	Upper Bound	Tolerance	VIF
1	(Constant)	4.534	0.373		12.146	0.000	3.799	5.269		1
	HER	0.260	0.084	0.276	3.310	0.001	-0.274	0.055	0.985	1.000
	a. Dependable Valuable: IQ									

5.10.5 Regression Analysis for Medical Error Reduction (MER)

Using hierarchical multiple regression, the moderating effect of medical error reduction (MER) on information quality (IQ) was examined. The outcome of the moderated regression analysis is displayed in Table 5.41. Figure 5.14 displays the histogram of the residuals in the regression model for the dependent variable, MER. It was found that the residuals histogram was very near the normal curve, proving that normality was acceptable.

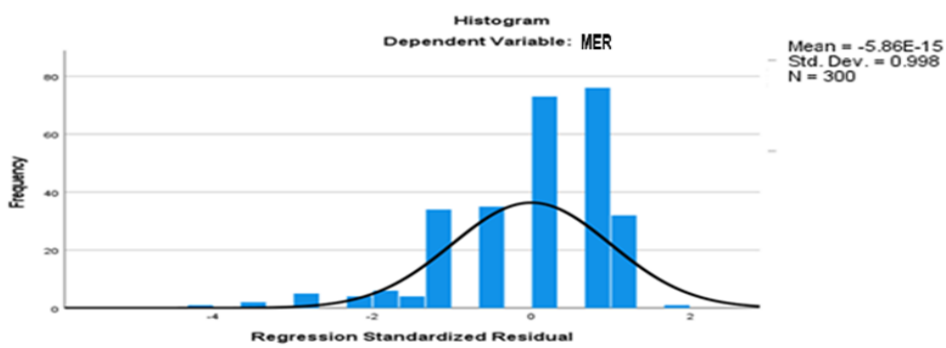


Figure 5.14: Histogram of standardised residuals for MER

A P-P plot of the residual for the MER regression model is shown in Figure 5.15. The normality assumption was confirmed because there were no significant deviations from normality in the residuals (Tabaschnick & Fidell, 2019).

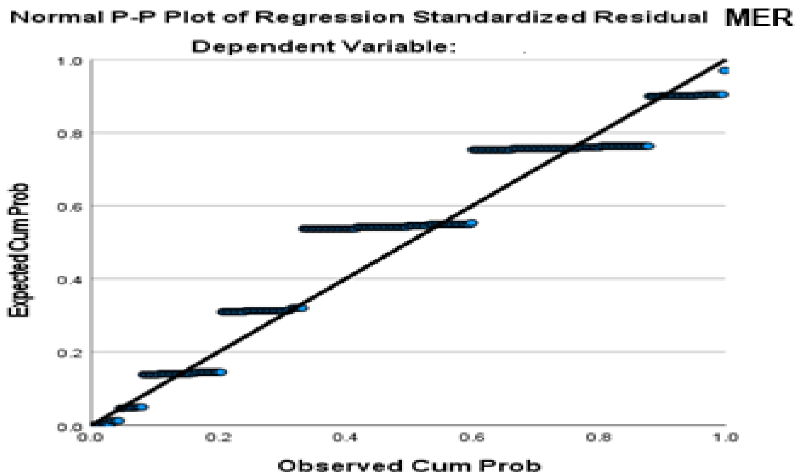


Figure 5.15: Normal P-P plot for the regression residual - MER

The model summary in Table 5.47 was created using the multiple regression analysis results. According to the findings, IQ was found to be adequate for explaining (MER). This conclusion was supported by the coefficient of determination ($R^2 = 0.000$), which indicated that IQ explained less than (0.1%) of the variation in the model. Table 5.47 contains a further evaluation of the model for the impact of IQ on MER based on the findings of the Analysis of Variance (ANOVA).

Table 5.47: Model summary for the regression model - MER

Model Summary									
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics				
					Square Change	F Change	df1	df2	Sig. F Change
1	.0.13	0.000	-0.014	0.28162	0.000	0.022	1	271	0.821
a. Predicators: (Constant), IQ									
b. Dependent Variable: MER									

The results demonstrated that the model was appropriate for further study and that IQ was a significant predictor of a decrease in MER. As shown in Table 5.48, the analysis of variance was used to determine the model's fitness (ANOVA). A statistically insignificant relationship between the constructs IQ and MER was found, as indicated by F (4.296) = 0.003, ($p>0.05$). ANOVA for regression analysis was further used to ascertain the moderating impact between IQ and MER, as shown in Table 5.48.

Table 5.48: ANOVA for the regression model - MER

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	0.003	4	0.003	0.034	.853
	Residual	21.521	295	0.079		
	Total	21.523	296			
a. Dependent Variable: MER						
b. Predictors: (Constant), KQ						

Table 5.49 shows the results of the regression coefficients. Each construct's importance in the model is indicated by the standardized. The results demonstrate a positive and statistically significant relationship between KQ and MER (β = 0.011, t= 0.185, p<0.05). Based on the results, the dependent variable, KQ, and the predictor, MER, have a statistically significant positive relationship, the research results show.

Table 5.49: Coefficients of the regression model – MER

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta	T	Sig.	Lower	Upper Bound	Tolerance	VIF
1	(Constant)	4.445	0.133		33.413	0.000	2.183	4.707	.180	3.000
	IQ	0.006	0.031	0.011	0.185	0.853	-0.055	0.066		
	a. Dependable Valuable: MER									

5.10.6 Regression Analysis for Evidence-Based Practice (EBHP)

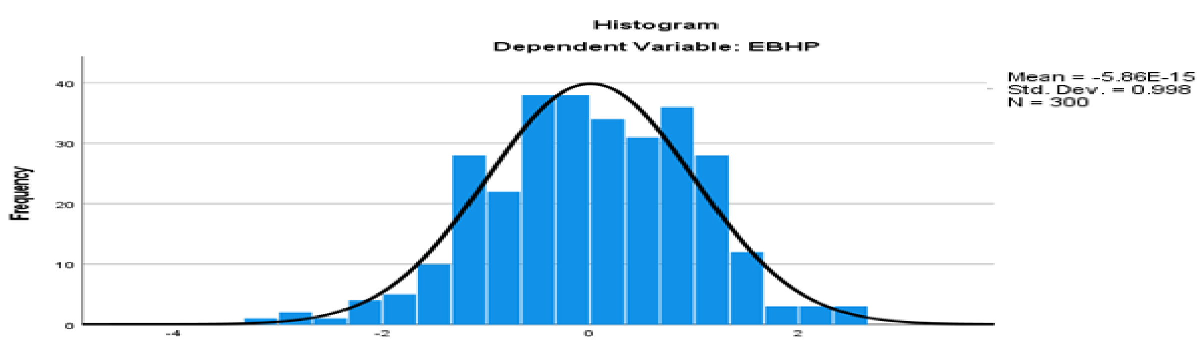


Figure 5.16: Histogram of standardised residuals for EBHP with the normal curve

It is assumed that residual errors in multiple regression are equally distributed and unrelated to one another (Field, 2016). The histogram and normal probability plots were produced to make sure the residual terms were normal. Figure 5.16 illustrates the histogram of the regression model with normal curves of EBHP which is a dependent variable. Based on the symmetric bell curve form that is not skewed and is therefore centered around the mean, the output shows that the residuals are normal (Tabaschnick & Fidell, 2019). According to the normality assumptions, the graph displays a normal residual distribution.

A typical P-P plot of the residuals for the regression model - EBHP is shown in Figure 5.17. For that reason, the straight diagonal line of the normal distribution is contrasted with the illustrated residuals. Hair et al. (2014) explains that the distribution is referred to as normal if the residual line coincides with the diagonal. The residuals have the appearance of a normal distribution because the residual values follow the diagonal with the least amount of deviation.

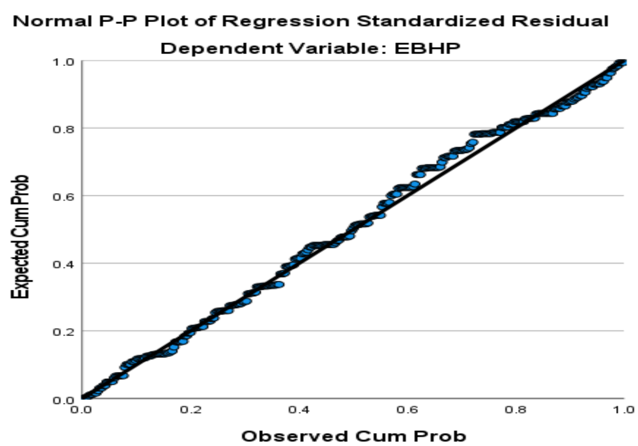


Figure 5.17: Normal P-P plot for the regression residual EBHP

The model summary shown in Table 5.49 is the result of the initial regression model evaluation. This resulted in the R^2 change, which showed the increase in variance accounted for by the new interaction term. R^2 increased by 0.159, indicating a (15.9%) increase in the amount of variation that the extra interaction term could explain. It is important to note that the increase in variety is statistically significant ($p<0.05$), suggesting that BCP, DTD do contribute to the adoption EBHP. The results of the Analysis of Variance (ANOVA) that mediated the adoption of the EBHP and had an impact on the variables DTD and BCP are presented in Table 5.50.

Table 5.50: Model summary for the regression model - EBHP

Model Summary										
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate	Change Statistics					
					Square Change	F Change	df1	df2	Sig. F Change	Durbin Watson
1	.399	0.159	0.154	0.47074	0.159	28.055	2	296	0.000	2.119
a. Predicators: (Constant), BCP, DTD										
b. Dependent Variable: EBHP										

According to Table 5.51, the model was statistically significant and suitable for further research. Analysis of Variance was used to evaluate the model's fitness (ANOVA). F (2.298) = 28.055, ($p<0.05$), showing that the model fit the phenomenon under study and that (BCP and DTD) all contributed to the adoption of EBHP. As can be seen in Table 5.51, regression analysis using ANOVA was used to ascertain the moderating impact between the dependent variable: EBHP and the predicators BCP and DTD)] (EBHP).

Table 5.51: ANOVA for the regression model EBHP

ANOVA						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	12.434	2	6.217	28.055	.000
	Residual	65.596	296	0.222		
	Total	78.028	298			
a. Dependent Variable: EBHP						
b. Predictors: (Constant), BCP, DTD						

The standardised coefficients for the predictor variables are displayed in Table 5.52. Hence the standardized coefficient displays the model contribution of each component. DTD and EBHP did not have a statistically significant relationship (β = 0.232, t = 4.063, ($p< 0.05$). However, the results also show a favourable and statistically significant relationship between organisational context (OC) and evidence-based practice (EBHP) (β = 0.231, t = 4.011, $p<0.05$). BCP and EBHP also have a positive and statistically significant relationship (β = 0.352, t = 4.401, $p<0.05$). According to the results, there is a statistically significant positive relationship between the dependent variable, EBHP, and the two predictors, BCP and DTD.

Table 5.52: Coefficients of regression model - EBHP

Coefficient										
Model		Unstandardized Coefficients		Standardized Coefficients	T	Sig.	95.0% Confidence		Collinearity Statistics	
		B	Std. Error	Beta			Lower	Upper Bound	Tolerance	VIF
1	(Constant)	1.994	0.289		6.910	0.000	1.426	2.561		
	DTD	0.226	0.056	0.232	4.063	0.000	0.116	0.335	0.370	2.150
	OC	0.231	0.033	0.231	4.011	0.000	0.112	0.323	0.360	2.134
	BCP	0.290	0.066	0.352	4.401	0.000	0.160	0.419	0.370	2.150
	a. Dependable Valuable: EBHP									

5.11 THE STRUCTURAL EQUATION MODELING (SEM)

The statistical method of choice is structural equation modeling (SEM), which is both well-liked and effective. SEM has recently been applied to business and public administration, as well as social sciences (De Carvalho & Chima, 2014). The postulated position and theorized linkages of each construct in relation to other constructs in the model are presented using structural equation modelling. The SEM process in this study follows Hair et al. (2022)'s two-step approach: first, specifying and assessing the measurement model to confirm validity, and then examining the structural model to examine the correlations between the components (Hair et al., 2019).

Furthermore, both processes required a review of the model fit indices and parameter estimations, which were evaluated using the same procedures and criteria as in the previous section's CFA analysis. It follows that, the structural model focuses on the relationships between the latent variables, while the confirmatory factor analysis model reveals the correlations between factors and indicators. The causal links of the latent items, including direct and indirect effects, were the most crucial components to identify in the hypothesized model. Thus, the Maximum Likelihood (ML) estimation approach was used to fit the final structural equation model. In every statistical analysis, the sample size plays a critical role (Lucko & Rojas, 2018). A sample size of 300 was appropriate for all regressions and other studies that formed the basis of the structural equation modelling model (Hair et al., 2019).

5.11.1 Structural Model Analysis

In general, the measurement model shows how constructs and indicators are related. A construct must be statistically represented by an item linked to the empirical data (indicators) because it cannot be observed directly (Rigdon & Sarstedt, 2022). This makes it possible to test construct-related hypotheses statistically. Figure 5.18 illustrates the measuring model. The figure depicts the relationship of a latent variable (construct) with another latent variable using double-headed arrows, as well as the connection between latent variables and observable variables (construct items) using single-headed arrows. Structural (path) coefficients are the figures on each path.

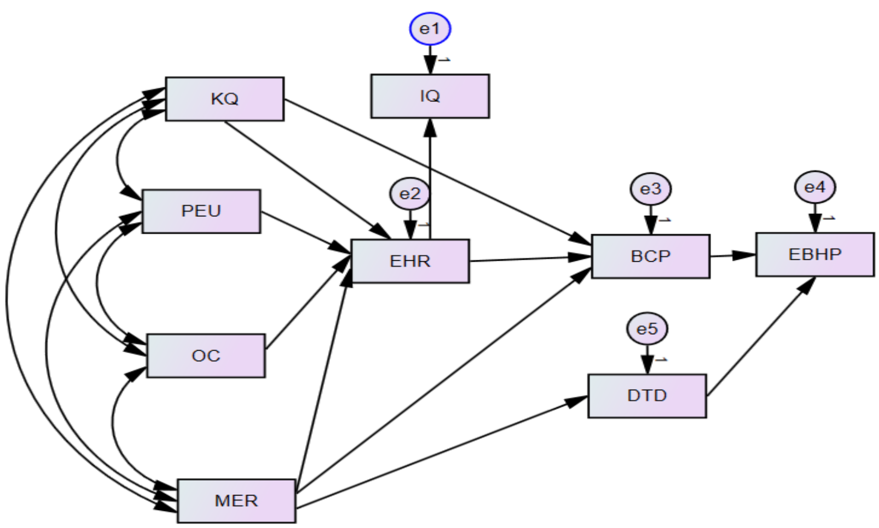


Figure 5.18: Structural model for evidence-based healthcare practice (unrefined)

These fit indices are probably affected by the model size as well, as mentioned in the literature on model size (Moshagen, 2012), as they are functions of the likelihood ratio (LR) chi-square statistic, which is typically upwardly biased in big models. The formal chi-square test is rarely used by applied researchers to evaluate specific SEM models; instead, they frequently rely significantly on practical fit indices. Therefore, it is crucial to know whether chosen fit indices tend to rise or fall when the model size rises in order to apply practical fit indices in the right way. Following the execution of the measurement model, the fit indices were extracted. Table 5.53 displays the fit indices' measurements from the AMOS output versus the corresponding threshold values.

Table 5.53: Measurement Model Fit Indices

Measurement Fit Indices	Obtained Measurement Model Value	Measurement Fit Indices' Threshold Level	Recommendations
χ^2	60.832	Ratio $2.1 \le (\chi^2 /\text{d.f}) \le 3.1$	χ^2/d. f is within the range of threshold, shows the model is good
D.f	19		
χ^2 /d.f	3.201		
RMSEA	0.07	0.05≤ (RMSEA) ≤ 0.080	Less than the threshold, shows the model is good
CFI	0.844	≥ 0.950	Less than the threshold, needs modification
GFI	0.944	≥ 0.90	More than the threshold, shows the model is good
SRMR	0.062	SRMR ≤ 0.08	Acceptable range 0 ≤ SRMR ≤ 0.09 but on the higher side.

Table 5.53 shows a ratio of χ^2/d. f = 60.832/19 = 3.2017 at p=0.000 significant at p <0.01. The probability less than 0.05 shows that if the null hypothesis is rejected, the model has a strong fit but may provide the least amount of error for the study's model, even though the ratio χ^2/d.f was within accepted parameters. As previously indicated, this measurement must be compared to other fit indices before the model may be changed (Dion, 2008; Barrett, 2007). The results were GFI = 0.944, CFI = 0.844, and RMSEA = 0.07. The CFI fit index was lower than the cut off, while the RMSEA was higher. As a result, before the hypotheses could be tested, the model needed to be refined.

5.11.2 Modification of measurement model

The measurement model was modified based on the GFI, CFI, and RMSEA values obtained by deleting and/or amending the observable variables that would not result in value distortion in the measurement model. To identify these indicators, the researchers combed through the AMOS output using Jöreskog and Sörbom's (1993) removal criteria. According to Jöreskog and Sörbom (2000), modification indices indicate the extent to which the χ^2 fit statistic decreases when a currently fixed parameter is released, and the model fit is reestimated. Large modification indices are defined as those that exceed 6.64, indicating current fixed parameters that, if freed, would improve model fit significantly. The covariance and regression weights output from AMOS, which were earmarked for modification or elimination, are shown in Tables 5.54 and 5.55.

5.11.3 Maximum likelihood estimates

Because the data was normally distributed, the maximum likelihood parameter estimation was chosen above other available estimation methods such as weighted least squares, two-stage least squares, and Varimax method. The chosen maximum likelihood method is iterative and tries to maximize the likelihood that attained criterion variable values will be predicted accurately, which the study considers important. The ordinary least square methods minimise the squared deviations between values of the criterion variable and those predicted by the model and are most commonly used for functional relationship modelling between variables (Mutan, 2004), whereas the chosen least square methods minimise the squared deviations between values of the criterion variable and those predicted by the model the study considered important.

Error Terms

An error term was added to each indicator in this investigation. The error terms were made up of arbitrary names beginning with the letter 'e' and ending with a numerical value. The single-headed arrows indicate causal relationships between constructs and the dependent variable (EBHP), whereas the double-headed arrows indicate covariances between variables (Byrne, 2012). Hox and Bechger (1998) further argued that introducing varied covariance between error components, which is dependent on modification indices, could improve model fit. The chi-square statistic should fall by the least amount possible if the relevant parameter is released, as indicated by the value of a modification index that could result in a significant improvement in fit. Due to a lack of theoretical reason, covariance between items is only done inside the same construct with the restriction of pairing it with other constructs. Freeing the parameters based on modification indices will increase the model fit at the cost of one degree of freedom, and a theoretical rationale is reviewed post hoc (Hox & Bechger, 1998). Covariance between error terms, based on modification indices (Hox & Bechger,1998) as shown in Table 5.54.

Table 5.54: Modification indices for covariance (Unrefined)

Error term			M.I.	Par Change
e1	<-->	e2	100.353	-1.549
e1	<-->	e3	21.071	-.313
e1	<-->	e5	12.634	.445

Modification indices for regression weights

The indication loadings are shown in Table 5.55. All the loadings of the mediating indicator (Diagnosis and treatment of diseases) with its associated latent variables (Organisational context and Perceived ease of use) were statistically significant, as stipulated in the model. Par Change ranged from.333 to.509, confirming that the predicted relationships between latent variables and their indicators.

Table 5.55: Modification indices for regression weights (Unrefined)

Path			M.I.	Par Change
Diagnosis and Treatment of diseases	<---	Organizational context	68.483	.333
Diagnosis and Treatment of diseases	<---	Perceived ease of use	120.107	.509

Table 5.12's error terms has the ability to raise the value of 2 and other fit indices. As demonstrated in Table 5.15, the error terms were connected to covariance. The covariance modification indices aid in the management of the value of chi-square (χ^2) by reducing it in relation to the degree of freedom (d.f). This means that as the χ^2 decreases, the degree of freedom must decrease as well as (d.f). If three error factors (e1, e2, and e3) are allowed to converge, their covariance should vary by lowering the modification indices of the structural model 2 hence resulting in an improved better model fit. According to modifying indices for regression weights is a better option than eliminating model parameters (Byrne, 2015). The model's fit indexes were all significant and within the acceptable range. Hence, the model fitness was achieved without deleting any parameters. If the null hypothesis is rejected, there is a larger likelihood than the 0.05 value threshold that the model does not fit, signalling that there could be a significant error margin.

5.11.4 Measuring the model fitness

After modification the measurement model was re-run, and new fit index values were extracted. Figure 5.9 depicts the final model with deleted and covariance construct items.

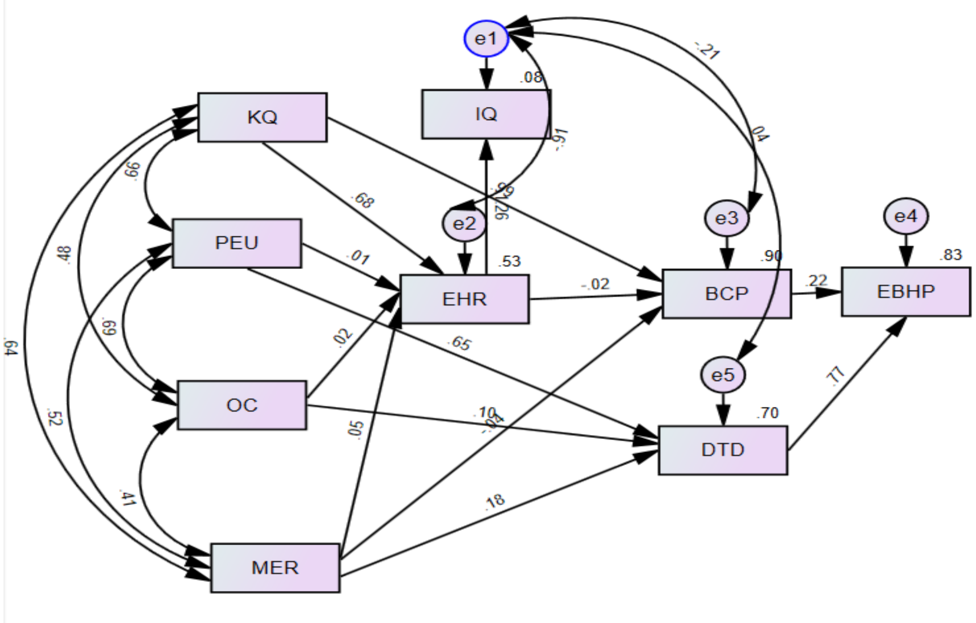


Figure 5.19: The final structural model for evidence-based healthcare practice

Table 5.56 shows the listed results of the measurements of the fit indices, as extracted from AMOS. In addition, the results reveal that the model fit was good according to two fit indices (χ^2/d. f and SRMR). The remaining fit indices (CFI, RMSEA, and GFI) were all below the threshold level, indicating that the measurement model should be tweaked further. Hence, the improved model produced a new set of results that were significantly superior. These new results were calculated using 50.755 chi-square statistics with 21 degrees of freedom (χ^2/d. f = 50.755/21 = 2.4169). Similarly, the revised output shows χ^2/d. f values that are close to the limits' lower bound, indicating a good fit. Confirmed fit indices also improved outputs, with all results indicating a satisfactory model fit. Further, the results indicated that the model was well-fitting, with RMSEA = 0.035, CFI = 0.905, GFI = 0.9996, and SRMR = 0.019. AMOS, on the other hand, proposed no more changes, implying that this was the model's best match. As SEM is a complicated method of analysis, it is acceptable to achieve a model fit using two or more fit indices (Kline, 2016; Hooper, Coughlan & Mullen, 2008).

Table 5.56: Model fit indices with their threshold values (Refined)

Measurement Fit Indices	Obtained Measurement Model Value	Measurement Fit Indices' Threshold Level	Recommendations
χ^2	50.755	Ratio 2.1 ≤ (χ^2 /d.f) ≤ 3.1	χ^2/d. f is within the range of threshold, shows the model is good
D.f	21		
χ^2 /d.f	2.417		
RMSEA	0.035	0.05≤ (RMSEA) ≤ 0.080	Less than the threshold, shows the model is good
CFI	0.905	≥ 0.950	More than the threshold, shows the model is good
GFI	0.996	≥ 0.90	More than the threshold, shows the model is good
SRMR	0.019	SRMR ≤ 0.08	Acceptable range 0 ≤ SRMR ≤ 0.09 but on the higher side.

The preceding section summarised the multiple fit indices and parameter estimates used to assess goodness-of-fit of the full latent variable model. The model was found to have an adequate fit on the basis of examining the collective statistical measures, as a result, additional specification of the model was not necessary. Figure 5.19 depicts a refined model with standardised loadings for each construct item. There are no more parameters that need to be deleted or modified in the figure.

5.11.5 Results of Hypotheses

The testing of hypotheses is presented in this section. In this study, the independent variables were IQ, KQ, MER, EHR, DTD, BCP and OC, whereas the dependent variable is EBHP. As mentioned by the decision rule in section 4.6.6, p-values (p<0.001; ** p < 0.01; * p < 0.05) have been used as the most relevant factor (decision rule) for testing the hypothesis. Table 5.57 below tests the study's hypotheses, which were developed in section 3.4.1.

Table 5.57: Summary of hypotheses testing results.

Hypotheses	Paths			Estimate (Beta)	S.E.	C.R.	P	Recommendation
H1	Information quality	<---	Electronic health records	0.289	.078	16.558	***	Supported
H2	Knowledge quality	<---	Electronic health records	.558	.044	16.476	***	Supported
H3	Information quality	<---	Medical error reduction	-.040	.022	-1.796	.072	Not Supported
H4	Medical error reduction	<---	Knowledge Quality	.048	.022	2.176	.030	Not Supported
H5	Better coordination	<---	Information quality	.087	.037	2.350	0019	Not Supported

Hypotheses	Paths			Estimate (Beta)	S.E.	C.R.	P	Recommendation
	of patient care							
H6	Better coordination of patient care	<---	Knowledge quality	.985	029	33.466	***	Supported
H7	Better coordination of patient care	<---	Electronic health records	-.020	.024	-.810	.418	Not Supported
H8	Better coordination of patient care	<---	Service quality					Not tested was dropped from the model
H9	Diagnosis and treatment of diseases	<---	Electronic health records	.0637	.045	14.014	***	Supported
H10	Diagnosis and treatment of diseases	<---	Medical error reduction	.124	.025	4.986	***	Supported
H11	Electronic health records	<---	Perceived usefulness					Not tested was dropped from the model
H12	Electronic health records	<---	Perceived ease of use	.021	.035	.586	.558	Not Supported
H13	Electronic health record	<---	Technical context					Not tested was dropped from the model
H14	Evidence-based healthcare practice	<---	Organisational context	.029	.026	1.123	.261	Not Supported
H15	Evidence-based healthcare practice	<---	Environmental context					Not tested was dropped from the model.
H16	Evidence-based healthcare practice	<---	Better coordination of patient care	.154	.019	7.902	***	Supported
H17	Evidence-based healthcare practice	<---	Diagnosis and treatment of diseases	.754	.028	27.056	***	Supported

Note: $\chi 2$ /d.f (10.174/8) = 1.272; *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; GFI = 0.995; CFI = 0.998, SRMR = 0.0149; RMSEA = 0.024

Note: p =0.253 which greater than 0.05.

5.12 CHAPTER SUMMARY

This chapter's objective was to provide the conclusions of the research data gathered from healthcare professionals who participated in the study. 300 of the 420 completed questionnaires were analyzed using the statistical software programs *SPSS (Version*

23.0). Further, tables were used to present a profile of the respondents, highlighting their gender, age, degree of education, work experience, and department they employed. Majority of the participants (225) were nurses. Finally, the hypothesis was tested to validate the final model. Since the overall model fit was good based on the results, no further modifications were needed. The seventeen (17) hypotheses were evaluated for statistical validity using the conceptual framework shown in Figure 3.2. In this study, correlations between the independent variables SQ KQ, PU, PEOU, TC, OC, EC, and the dependent variables EHR, MER, IQ, DTD, BCP and EBHP were examined. The following seven of the seventeen hypotheses were rejected: H3, H4, H5, H7, H12, and H14. The following chapter will detail the study's results. The study's theoretical and practical contributions are also covered in this chapter. Prior to the conclusion, the study's limitations and the need for additional research are also discussed.

CHAPTER 6: DISCUSSION, INTERPRETATION, CONCLUSION AND RECOMMENDATIONS

6.1 INTRODUCTION

The previous chapter discussed the interpretation of the results in relation to the literature reviewed, research objectives, research questions and research hypothesis. This chapter serves as the final chapter of this thesis. In addition to discussing the research model that was developed, it also provides a summary of the research findings. Furthermore, the study's contribution to the body of knowledge, as well as its implications for future research and practice, are also covered in this chapter. Finally, it discusses the study's shortcomings and offers suggestions for further research.

6.2 DISCUSSION AND INTERPRETATION OF FINDINGS

This section discusses and interprets findings in relation to the six research objectives stated in Chapter 1 and covered in Sections 6.3.1 to 6.3.8. In this study, which used DGMAH as a case study hospital, the critical success factors for adoption of evidence-based healthcare practice (EBHP) at a South African public hospital were investigated. The framework for this thesis was developed based on the updated D&M IS Success Model, the technology-organisation-environment framework (TOE) and the technology acceptance model (TAM) as the underpinning theories. Six constructs, namely, electronic health records (EHR), medical error reduction (MER), information quality (IQ), service quality (SQ) and knowledge quality (KQ) were adopted from the D&M IS Success Model. TAM has two constructs: perceived usefulness (PU) and perceived ease-of-use (PEU). Regarding TEO, three constructs: technical context (TC), organisation context (OC) and environment context (EC) were adopted.

Hypotheses were established based on the conceptual framework, with many modifications made to the constructs to allow the researcher, to investigate the critical success factors for the adoption EBHP. Figure 3.2 shows the conceptual model and proposed relationships between the dependent variable: EBHP, mediating variables: DTD and BCP, independent variables: EHR, MER, IQ, SQ, KQ,PU,PEU,TC,OC and EC.

In structural equation modelling (SEM), latent variables are not directly observed but are inferred by the covariation among a set of observed variables (also called reflective indicators). A quantitative survey of healthcare professionals was carried out at DGMAH. Twelve physicians, 225 nurses, eight radiologists, eight chemists, and eight physiotherapists made up the study's sample population. In total, 300 healthcare professionals took part in this study. For this study, the population sample of healthcare professionals was drawn using convenience sampling, also known as incidental sampling or grab sampling. The objectives for the study's research and the associated hypotheses will be addressed in the section that follows.

6.2.1 **Research Objective 1:**

- To identify the critical success factors that determine the contructs that inflence the adoption of evidence-based healthcare practice at a South African public hospital.

To address the RO1, a conceptual framework was developed, based on the updated D&M IS Success Model which included TOE and TAM, to identify the generating constructs for the adoption and implementation of EBHP as previously reported. Questionnaires were issued to healthcare professionals to collect data. Several hypotheses based on the model were generated and analysed to uncover the influencing factors for the adoption of EBHP at a South African public hospital. Alongside, several research papers and journal articles have been published on the impact of EHR on IQ, KQ, DTD, BCP on EBHP were also reviewed.

Hypotheses **H1, H2, H9, H16 and H17** addressed RO1 and Sections 2.6.1–2.6.12 included literature reviewed to support the findings of these hypotheses. To help address this sub-objective, regression analysis was performed in Sections 4.3.2.1 and 4.3.2.2; correlations were investigated in Section 4.3.1.

H1: There is a significant positive relationship between electronic health records (HER) and Information quality (IQ): Supported.

The results in Table 5.56 show that EHR and IQ have a positive and significant relationship ($\beta=0.289$; $p < 0.05$). An insignificant negative relationship between EHR and IQ was found by the correlation test ($r = 0.154$; $p > 0.05$) as shown in Table 5.26. However, Table 5.46 shows that the regression test has a significant relationship between the two variables ($\beta = 0.027$; $p < 0.05$). EHR had a significant direct effect on IQ as hypothesised in Figure 3.2. According to the study's findings, EHR have the potential to improve the standard of healthcare by facilitating timely access to patients' medical records, monitoring patients over time to make sure they receive treatment that is recommended by guidelines and providing decision-support tools to reduce medical mistakes. For this reason, hypothesis H1 was supported.

Findings of this study corroborate those of Rahman, Strawderman, Lesch, Horrey, Babski-Reeves and Garrison (2018); Esen and Erdogmus (2016) who found that optimism affects perceived ease of use. This is in line with the research by Meeks, Takian and Sittig (2018) who found that the adoption of EHR may have a considerable effect on patient quality and safety. Furthermore, healthcare managers and policy analysts must consider patient satisfaction to enhance the healthcare system and guarantee that patients receive the level of treatment they demand (Ahmed & Van der Schaar, 2017). An EHR is necessary to revolutionise clinical care in a way that would improve patients' well-being. The improvement of medical records, the elimination of unnecessary lab tests and prescriptions and finally, the accuracy of drug dosages all contribute to the improvement of patients' health (Da Silva & Krishnamurthy, 2018).

H2: There is a significant positive relationship between electronic health records (EHR) and knowledge quality (KQ) Supported.

Figure 5.19 indicates that EHR and KQ have a positive and significant relationship ($\beta=0.558$; $p < 0.05$). The correlation test ($r = 0.181$; $p < 0.05$) also revealed a significant positive relationship between EHR and KQ (Table 5.26). Table 5.43 shows that the regression test has a statistically strong relationship between the two variables ($\beta = 0.137$; $p < 0.05$). According to this study, the integration of knowledge quality into electronic health records may reduce prescription errors by improving access to pertinent data, enhancing coordination of treatment among various providers and visits, and streamlining the documentation and monitoring process. For this reason, hypothesis H2 was supported. This finding supports Uluc and Ferman's (2016) claim that EHR facilitates accurate and timely communication between all healthcare providers (Zayyad & Toycan, 2018). In addition, using EHR systems increases organisational efficiency, process quality and decision-making capabilities and promotes evidence-based practice recommendations as well as the possibility of uncovering improved practice standards (Bardhan & Thouin, 2017).

The findings of this study are consistent with those of Ayabakan, Bardhan, Zheng, and Kirksey (2017), who investigated the effects of health information exchange for patients with congestive heart failure in hospital outpatient clinics and found that doing so reduces the frequency of radiology and laboratory testing. Further evidence for this is offered by Gordon, Leiman, Deland and Pardes (2014) in a discussion about how healthcare professionals can monitor patients' health and initiate early intervention, when appropriate, by utilising the EHR system's capabilities.

H9: There is a significant positive relationship between medical error reduction (MER) and diagnosis and treatment of diseases (DTD): Supported.

Table 5.56 shows that there is a positive and significant relationship between MER and DTD ($\beta = 0.163$; < 0.05). Evidence illustrates that, the correlation test demonstrated a substantial positive relationship between MER and DTD ($r = 0.173$; $p<.005$) in Table 5.26. Table 5.40 shows that the regression test found an insignificant relationship between the two variables ($\beta = 0.054$; $p > 0.05$); on the other hand, H9 was supported. The findings of this study corroborate those of Adenuga, Kekwaletswe, and Coleman (2015) who hypothesised that the use of electronic records would allow for the distribution of up-to-date health information across a variety of services to enhance medical practice.

According to the conclusions of this study, medical errors can be caused by typographical errors, which can be reduced by using digital record keeping. Gartlehner and Matyas (2016) posit that shared decision-making is a characteristic of effective clinical practice, honouring patients' right to know that their informed choices should be at the centre of all medical activities (Hoffmann, Legare, Simmons, McNamara, McCaffery, Trevena & Del Mar, 2016). Conversely, the findings of this study are consistent with those of Cebul, Love, Jain and Hebert (2018) who discovered that using EHR reduces typographical errors by providing grammatical checks and underlining confusing content.

H16: There is a significant positive relationship between better coordination of patient care (BCP) and evidence-based healthcare practice (EBHP): Supported.

Figure 5.19 indicates that there is a positive and significant relationship between BCP and EBHP ($\beta=0.154$, $p<0.05$). The correlation test ($r=0.154$, $p<0.05$) demonstrated a strong, significant relationship between greater BCP and EBHP (Table 5.26). Table 5.52 shows the estimates or coefficients of the regression analysis. As demonstrated in Table 4.13, there is a positive significant relationship between the two constructs ($\beta= 0.352$; $p<0.05$). These findings are in line with those of Faber, Grande, Wollersheim, Hermens, and Elwyn (2014), who noted that evidence-based practice advocates for basing every choice on the best available data while also considering the preferences of the patient. They argue that additional study is necessary to support negative findings. H16, however, was supported. Hence, the results of the supported hypothesis demonstrate that using EBHP is necessary to deliver safe, high-quality patient care. Nurses and other healthcare professionals can give patients the best, most affordable care by utilising evidence-based healthcare practices. It follows that, the findings of this study support the claims made by Krist, Beasley, Crosson, Kibbe, Klinkman, Lehmann, and Waldren (2014) that the adoption of an EHR system can facilitate health information exchange by fostering the sharing of clinical information and patient care coordination among healthcare providers, potentially leading to a higher patient quality of care.

The findings of this study also concur with those of Jamoom, Patel, Furukawa, and King (2014), who discovered that physicians who utilise EHR had increased clinical workflow efficiency and patient safety, resulting in fewer medical errors and better patient care. 82% of EHR users reported that the quality of clinical choices has improved, eighty-six percent reported a decrease in prescription errors, and another 14% reported an improvement in patient preventative care (Bardhan & Thouin, 2017). Thus, the study's findings concur with those of Nguyen, Bellucci, and Nguyen (2014), who claimed that an EHR system can handle enquiries originating from laboratory test results as well as patients' historical data, allowing doctors to follow up on patients' test results.

H17: There is a significant positive relationship between diagnosis and treatment of diseases (DTD) and evidence-based healthcare practice (EBHP): Supported.

Table 5.56 shows that there is a positive and significant relationship between DTD and EBHP (β =0.754, $p < 0.05$). The correlation test revealed a strong positive relationship between DTD as well as EBHP ($r = 0.299$; $p < 0.05$) in Table 5.26. Table 5.52 shows that the regression test found a significant association between the two variables (β =0.232; $p < 0.05$). DTD had a significant direct effect on EBHP, as hypothesised in Figure 3.2. For this reason, Hypothesis H17 was supported. Patients felt more at ease expressing and discussing treatment preferences when their doctor specifically welcomed them to do so; when they were taken seriously and listened to and when the doctor was willing to answer questions. These findings are consistent with Pyrene's (2015) claim that access to medical records is important since, in practical terms, it is difficult for medical professionals to offer the best diagnosis or treatment without it.

Access to accurate and thorough patient health information is necessary for the ongoing provision of healthcare services. This finding is in line with that by Yazdi-Feyzabadi, Emami and Mehrolhassani (2015) who found that medical records are a useful entity that improves patient care while also encouraging the generation of vital data for use in decision-making at every level of the healthcare system. It is crucial for the healthcare professional to be aware of previous diagnoses and whether they were successful. The research's findings confirm earlier findings from Chukmaitov, Harless, Bazzoli, and Deng (2017) which demonstrated how time and money may be saved by using the patient's medical history to make the proper diagnoses (Chukmaitov et al., 2017).

6.2.2 Research Objective 2:

- To determine the influence of electronic health records on medical error reduction, as well as on the diagnosis and treatment of diseases.

Hypotheses **H3, H4 and H10** addressed RO2 and Sections 2.6.1–2.6.12 included literature reviewed to support the findings of these hypotheses. To help with addressing this sub-objective, regression analysis was done in Section 4.3.2.3 and correlations in Section 4.3.1, to assist in answering this sub-objective.

H3: There is a significant positive relationship between electronic health records (EHR) and medical error reduction (MER): Not supported.

The results in Table 5.56 show a negative and insignificant relationship between the implementation of EHR and MER ($\beta=0.221$; $p > 0.05$). The correlation test ($r=0.254$; $p>0.05$) however, demonstrated a strong positive relationship between EHR and the MER (Table 5.26). Table 5.49 shows that the regression test found a significant association between the two constructs ($\beta = 0.011$; $p<0.05$). For this reason, hypothesis H3 was not supported. Particularly hospitals rely on data and information generated by knowledge management, knowledge exchange, and knowledge systems for making decisions. In this study, there are conflicting opinions in the research examining the significance of EHRs in improving patient health outcomes.

According to the study's findings, there are divergent views regarding the importance of EHRs in improving patient health outcomes. EHR systems, on the other hand, excel at supporting doctors, reducing human medical errors, raising standards of care, enhancing patient care, and improving health outcomes (Sebetci, 2018). Similarly, Akhlaq, McKinstry, Muhammad and Sheikh (2016) found a relationship between efficient information exchange and a lower risk of drug and medical errors. However, it is in contrast with the conclusions of earlier research by Kooij, Groen and Van Harten (2018) which showed that the implementation of HIE systems offers a platform for informing patients about their healthcare needs, particularly regarding available alternatives. The findings reinforce earlier research by Reis, Bonetti, Bottacin, Reis, Souza, Pontarolo, Correr and Fernandez-Llimos (2017) that showed enhanced clinical decision-making, communication and documentation are also related to patient safety. Based on research, diagnostic errors are frequently under reported or poorly reported National Academies of Sciences, Engineering, and Medicine (2015), which can help resolve the contradictory results of this hypothesis H3. Identifying or hiding underlying reasons may be challenging due to the unrecorded specifics of individual cognition and patient-clinician interactions.

H4: There is a significant positive relationship between knowledge quality (KQ) and medical error reduction (MER): Supported.

Table 5.56 shows a negative and insignificant relationship between KQ and MER ($\beta=0.048$; $p<0.05$). The correlation test demonstrated an insignificant negative relationship between KQ and MER ($r=0.181$; $p<0.05$) in Table 5.26. Table 5.43 shows the estimates or coefficients from the regression study. In addition, the regression test's findings indicated that there was no statistically significant correlation between the two constructs ($p>0.05$; $\beta=0.016$). This finding would imply that, although real diagnostic mistake rates in clinical practice are hard to establish, it is generally believed that 10% to 15% of all diagnoses are wrong (Eramus & Van der Walt, 2015). Pelaccia, Messman, and Kline's (2020) study, also discovered that diagnostic mistakes are acknowledged as the most frequent sources of charges of negligence in the pre-hospital emergency care context and contribute to a high fatality rate annually in the world, further supports these findings. However, hypothesis H4 was supported.

The supported hypothesis' findings also concur with those made by Gagnon, Payne-Gagnon, Breton, Fortin, Khoury, Dolovich, and Archer in (2016); Palabindala, Pamarthy, and Jonnalagadda in (2016) Using electronic health records (EHR) reduces medical errors, which is linked to improved patient safety and treatment quality. As patient data is so easily accessible, Campanell *et al.* (2015) concluded that EHRs give healthcare providers the best chance to diagnose, share, and retrieve information. Similar conclusions were found by Wani and Malhotra (2018), who noted that EHR has, on average, led to a 3% decrease in the length of hospital stays overall and the rate of readmissions, especially in patients with comorbid diseases. This result is consistent with statements made by Menon *et al.* (2016) and Zeng (2016) that the primary objective of an EHR system is to ensure that patients receive high-quality medical treatment.

H10: There is a significant positive relationship between electronic health records (EHR) and diagnosis and treatment of diseases (DTD): Supported.

The adoption of EHR has a significant positive relationship on DTD, as shown in Table 5.56 (β =0.124; p <0.05). In Table 5.26, the correlation test revealed a significant positive relationship (r =0.199; p<0.05) between EHR and DTD. Table 5.40 shows an insignificant relationship between the two constructs (β=-0.010; p > 0.05) for the regression test. EHR has a significant direct effect on DTD, as hypothesised in Figure 3.2 and for this reason, hypothesis H10 was supported. However, these findings study suggest that reducing medical errors will reduce the costs associated with unnecessary tests and treatments. Evidence from literature, indicate that, these findings corroborated those by Palabindala, Pamarthy and Jonnalagadda (2016); Pelland, Baier and Gardner (2017) who found that adopting EHRs reduce the risk of medical errors, which is associated to enhanced patient safety and quality of care. In a meta-analysis, Campanella, Lovato, Marone, Fallacara, Mancuso and Ricciardi, 2015) discovered that using an EHR resulted in a low rate of medical errors.

According to Khwima et al. (2017), technology makes it possible to collect data more accurately, improving the accuracy of patient records and influencing how the quality of care is handled when patients are hospitalised. As a result, it promotes higher safety by offering better care, like medical attention. Clinical practitioners need details on a patient's diagnosis, prior treatments, prescribed drugs, and progress to decide on the next steps in their treatment. If clinical health records are handled improperly, retrieving patient records may take a long time. This could prevent medical facilities from providing services or, even worse, result in the provision of incorrect treatments. The results of earlier studies by Ben-Assuli, Sagi, Leshno, Ironi, and Ziv (2015) agree with these findings. It was further emphasized that, both the medical professional and his patients benefit from a thorough medical record.

6.2.3 Research Objective 3:

- To evaluate the impact of information quality, service quality, knowledge quality as well as better coordination of patient care towards the adoption and implementation of evidence-based healthcare practice.

Hypotheses **H5, H6** and **H7** addressed RO3 and Sections 2.6.1–2.6.12 included literature reviewed to support the findings of these hypotheses. To help address this sub-objective, Regression analysis was done in Section 4.3.2.3 and correlations in Section 4.3.1, to assist in answering this sub-objective.

H5: There is a significant positive relationship information quality (IQ) and diagnosis and treatment of diseases (DTD): Supported.

Table 5.56 shows that there is a positive and significant relationship between IQ and DTD (β=0.087; $p < 0.05$). The correlation test demonstrated an insignificant negative relationship between IQ and DTD (r =-0.034; $p > 0.05$) in Table 5.26. On the other hand, the regression test demonstrated that the two variables have no meaningful association. Table 5.37 shows the results (β=0.080; $p > 0.05$). For that reason, findings could be considered inconsequential because certain diagnoses can be made in a matter of days, while others take months to be identified. This conclusion is further corroborated by Zayyad and Singh (2018), who noted that most diseases develop gradually over time, and that patients' symptoms may not appear for some time after the commencement of the disease. It may also take some time before a patient's symptoms are recognised as belonging to a certain diagnosis.

H5 was, nevertheless supported. The supported hypothesis' findings are consistent with Ngidi's (2015) assertion that patient records serve as a communication tool in healthcare settings by disseminating a variety of patient data, including the patient's medical history and the care they received from clinicians. When decisions are made without a thorough clinical medical history of the patient, their allergies, medications, and other pertinent medical information, medical errors may result (Wager, Lee & Glaser, 2017). Yanamadala, Morrison, Curtin, McDonald, and Hernandez-Boussard (2016) contend that faster diagnosis will result from EHRs' increased efficiency.

H6: There is a significant positive relationship between knowledge quality (KQ) and better coordination of patient care (BCP): Supported.

Table 5.56 shows that there is a positive and significant relationship between KQ and BCP (β=0.985; p <0.05). In Table 5.26, the correlation test showed a significant positive relationship (r=0.154; p.<005) between KQ and BCP, indicating that knowledge sharing among medical professionals has a positive impact on managing patient health outcomes. Table 5.37 shows the estimates or coefficients of the regression analysis. Moreso, the results show that there is no significant association between the two constructs (β = 0.043; p > 0.05); nonetheless, hypothesis H6 was supported. The results of this study suggest that shared healthcare decisions will enhance coordination between primary care and specialist care providers, result in accurate diagnosis, and result in effective treatment. This finding is in line with previous research on the adoption of technological innovation (Shaltoni, 2017). Similarly, the findings of this study imply that higher knowledge quality often leads to improved patient care coordination. Therefore, the findings of the study reaffirm a positive relationship between knowledge quality and better coordination of patient, hence resolving the issue of contradictory findings in the literature.

Since doctors make up the majority of those employed in hospitals, they are highly knowledgeable professionals whose decisions are frequently based on their knowledge and experience (Berghout, Fabbricotti, & Buljac-Samardzk, 2017). As a result, their theoretical and practical knowledge is essential for making clinical decisions about patient care. This is in line with the findings of Olatokun (2020) who claimed that because it can be challenging to establish the appropriate course of therapy for patients, medical professionals' tacit knowledge is more significant than their explicit knowledge. The bulk of clinical judgements and diagnostic procedures, according to Dietel (2017), Olatokun (2020) are based on tacit knowledge.

H7: There is a significant positive relationship between electronic health records (EHR) and better coordination of patient care (BCP): Not supported.

Table 5.56 displays an insignificant relationship between EHR and BCP (β=0.029; p >0.05). However, the correlation test demonstrated a strong significant relationship between EHR and BCP (r = 0.122; p <0.05) as shown in Table 5.26, while Table 5.37 shows that the regression test found a significant association between the two variables (β=0.125; p< 0.05). EHR did not have a significant direct effect on BCP as hypothesised in Figure 3.2. As a result, the results of this study show that BCP is not influenced by EHR. For this reason, Hypothesis H7 was not supported. Furthermore, these findings contradict previous research. According to studies (Arndt, Beasley, Watkinson, Temte, Tuan, Sinsky & Gilchrist, 2017), the effectiveness of the documentation in electronic health records (EHRs) is crucial to the calibre of interactions between primary care physicians and their patients.

In support of Arndt et al. (2017), conclusion that EHR has made it simpler to integrate patient medical histories for safer and better medical planning and planning and treatment. This is in line with findings of Kern, Edwards, and Kaushal (2016) who found that manual records in bulk data processing are exceedingly time-consuming and unreliable, to the point that the cost of retrieving such data might outweigh the apparent benefits. The results of hypothesis H7, inconsistent findings, could be explained by the fact that implementing EHRs is difficult in developing countries due to a lack of funding, infrastructure, knowledge, accessibility, and other factors (Aldredge, Rodriguez, González & Burt, 2020). These limitations present challenges for the healthcare system. According to Kumar and Mostafa (2019), there is broad consensus that EHRs can facilitate and collect data for use in population and patient centered health care delivery.

6.2.4 Research Objective 4:

- To explore the impact of technology-organisation-environment framework (TOE) framework factors towards the adoption and implementation of electronic health records (EHR).

Hypotheses H14 addressed RO4 and Sections 2.6.1–2.6.12 included literature reviewed to support the findings of these hypotheses. Further analysis was required to help address this sub-objective; regression analysis was done in Section 5.81-5.8.6 and correlations in Section 5.6 to assist in answering this sub-objective.

H14: The adoption of electronic health records (EHR) is positively influenced by top management support: Not supported.

Table 5.56 shows that there is a negative, insignificant relationship between top management engagement and electronic health record adoption ($\beta=0.029$; $p > 0.05$). The correlation test demonstrated a strong, significant relationship between top management support and electronic health record adoption ($r = 0.122$; $p < 0.05$) in Table 5.26. As shown in Table 5.52, the regression test demonstrated a significant association between the two variables ($\beta=0.231$; $p < 0.05$). For this reason, hypothesis H14 was not supported. Hence, the results of the study demonstrate that top management support has an insignificant influence on the adoption of electronic health records in public hospitals. This result contradicts prior research which demonstrated that leadership roles influence effective implementations in a variety of situations (Aarons, Ehrhart, Farahnak, Sklar, 2018).

In other words, the opinions of Moulin, Ehrhart and Aarons (2017) that top management sets the tone and agenda for strategic efforts that include the introduction of new technology and services, reinforce this argument. Numerous studies that have been examined emphasised the significance of top management support as a crucial element in the effective adoption of healthcare-related information systems, particularly in African countries (Namakula & Kituyi, 2014; Tetteh, 2016). Aaron et al. (2018) asserts that senior managers can have an impact on the adoption and use of new technologies by allocating time to the technology in proportion to its costs and potential, reviewing plans, keeping track of results, and assisting with management issues related to integrating the technology with the business' management process. Top management support, according to Dong, Xu, and Zhu (2016), promotes favourable user views, stimulates technology use and higher user performance, and increases the uptake of technology generally.

6.2.5 Research Objective 5:

- To determine the influence of ease of use and perceived ease of use towards the adoption and implementation of electronic health records (EHR).

Hypotheses **H12** addressed RO5 and Sections 2.6.1–2.6.12 and included literature reviewed to support the findings of these hypotheses. To help address this sub-objective, regression analysis was done in Section 4.3.2.3 as well as correlations in Section 4.3.1, to assist in answering this sub-objective.

H12: There is a significant positive relationship between perceived ease of use (PEU) and the adoption electronic health records (EHR) at a South African public hospital: Not supported.

According to the findings in Table 5.56 EHR and PEU have a negative and negligible relationship ($\beta=0.021$, $p > 0.05$). The correlation coefficient between the two variables is ($r= 0.158$, $p >0.05$) in Table 5.26. Table 5.34 presents the estimates or coefficient regression analysis. Not only but also EHR and PEU were statistically insignificant ($\beta=0.209$, $p <0.05$), according to the findings. PEU did not have a significant direct effect on electronic records adoption, as hypothesised in the original technology acceptance model as well as in Figure 3.6. For this reason, Hypothesis H12 was not supported. This finding is in contradiction with that by Huang, Teo and Zhou (2020) who discovered a significant correlation between attitude and PEU in the context of physician acceptance of EHRs.

The results of the current study are inconsistent with those of earlier studies conducted by Hoogenbosch, Postma, Janneke, Tiemessen, van Delden and Van Os-Medendorp (2018); Tavares and Oliveira (2017) in which it was discovered that perceived ease of use indirectly influences the intention to use electronic health records (EHRs) through attitude. In addition, the findings of other studies (Faustino & Simes, 2020; Singh & Sinha, 2020) who noted that perceived ease of use and perceived usefulness had a positive impact on an organisation's ability to adopt the Internet of Things (IoT) for a variety of uses, validated the findings of this research study, which concluded that perceived usability has a positive impact on the adoption of information systems. These findings may suggest that the performance and effort expectations connected to the adoption of

EHR in public hospitals are unlikely to have an impact on that decision for the sample under study. More study is required to examine the connection between perceived ease of use and EHR adoption in light of these conflicting results.

6.2.6 Research Objective 6:

- To determine the relevant critical success factors for developing a conceptual framework for the adoption of evidence-based healthcare practice at a South African public hospital.

A final model that intends to address the critical success for the adoption of EBHP at a South African public hospital was subsequently developed, as shown in Figure 6.1. Hypotheses that were accepted are those that are included in this model. SEM was used to validate and test the research model.

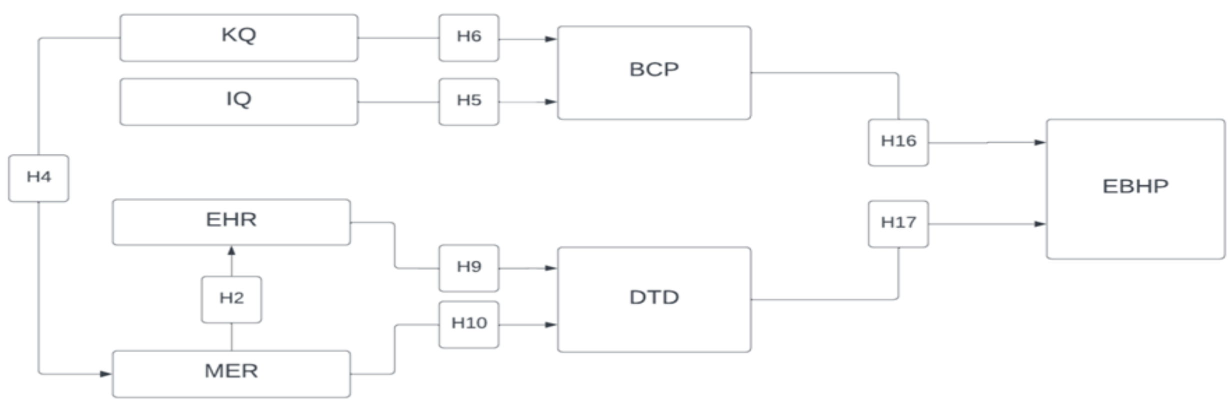


Figure 6.1: Evidence-based healthcare practice model

Source: Author's own research

In addition, the model demonstrates the relationships between the independent (KQ, IQ, EHR, and MER), mediating (BCP, DTD), and dependent (EBHP) variables that led to the development of an EBHP framework. EBHP framework is composed of the accepted hypotheses H1, H2, H4, H5, H6, H9, H10, H16, and H17. Table 5.56 indicates that nine of the eleven hypotheses contributed statistically to the framework. With values of (β=0.558, (p< 0.05), (β=0.558, (p< 0.05), and (β=0.558, (p <0.05), IQ, KQ and DTD are all significantly positively influenced by EHR, respectively. DTD significantly influences EBHP while having a significant positive impact on MER (β =0.558, ($p< 0.05$) and vice versa.

The study established that the adoption of EBHP is significantly and positively related to BCP ($r=0.294$; $p<0.05$), BCP ($r=0.299$; $p<0.05$). EHR is positively and significantly related to BCP ($r= 0.121$, $p<0.05$), DTD ($r=0.173$, $p<0.05$), IQ ($r= 0.221$, $p<0.05$) and IQ ($r=0.181$, $p<0.05$). The critical success factors for the EBHP, accounted for 19.8%, 17.7% and 17.2%, respectively, are revealed in the combined success factors' regression output regressed on predictors BCP, IQ and DTD. According to Field (2013) the findings point to a suitable model fit. In addition, the correlation in this model was found to be reasonably acceptable and acceptable with a Durbin-Watson value of 1.840.

Healthcare professionals' expertise is based on patient assessment, laboratory data and outcome data as well as patients' preferences and values, according to the conclusions of the defined framework of EBHP. There is no magic formula for weighing any of these factors; institutional implementation of EHR has a significant impact on IQ (updated patient medical records), KQ and EBHP implementation (the sharing of patient medical records among the healthcare professionals) provides a platform to make an informed decision on the DTD. The findings of the study suggested that DTD has a positive significant influence on BCP. Care coordination entails planning patient care activities and sharing information among all parties involved in the patient's care, to provide safer and more effective care. This means that the patient's requirements and preferences are anticipated and conveyed to the relevant individuals at the appropriate time and that this knowledge is used to provide the patient with safe, appropriate, and effective treatment. Furthermore, EBHP is a problem-solving approach to healthcare delivery that combines the best evidence from well-designed studies and patient-care data with patient preferences and values, as well as the knowledge of healthcare professionals.

6.3 THEORETICAL, METHODOLOGICAL AND PRACTICAL CONTRIBUTIONS OF THE CONCEPTUAL FRAMEWORK

This thesis' framework offers theoretical, methodological, and practical contributions. Below are descriptions of each contribution.

6.3.1 Theoretical contributions of the conceptual framework

This study identifies and investigates the critical success factors that support the adoption of evidence-based healthcare practice in the public health sector, in order to fill this gap. A 34-item questionnaire was developed and validated by the researcher in Chapter 5 to establish the constructs that might affect the adoption of evidence-based healthcare practice (EBHP). The method of developing the data collection instrument included reviewing pertinent literature for empirical studies, choosing appropriate items, pilot testing, and ultimately, empirical testing. Furthermore, the validation of the developed instrument scales required multiple procedures, as explained in the next paragraph.

Exploratory factor analysis (EFA) was used to identify the dependent construct: EBHP and then confirmatory factor analysis (CFA) was used to validate the underlying structure of the instrument's main constructs, as well as to assess composite reliability and construct validity. Using two reliability indicators (Cronbach's alpha and composite reliability), high levels of internal consistency were reported across all constructs. Convergent and discriminant validity were likewise strong in the constructs of the final proposed instrument. For this reason, it is expected that researchers in other developing countries with similar cultures and contexts will be able to utilise this instrument with confidence.

This research has contributed to the development of a new framework that identifies the critical success factors for EBHP adoption. The developed conceptual framework served as the foundation for the development of a questionnaire, which served as the data collection instrument, to evaluate the critical success factors for the adoption of EBHP at DGMAH from healthcare professional's perspective. In this study the hybrid model, was developed based on updated D&M IS Success Model, TAM and TOE framework. Furthermore, the information systems (IS) success model was employed in this study because it is the most comprehensive model for researching and measuring information system success and evaluation in the IS field. TAM was used for this study because it focuses on individual users' perceptions of technology and evaluates how those perceptions may influence their behaviour intention. TOE presents an organisational-level framework for technology adoption models that take factors such as top management support, infrastructure, and vendor support into account in the context of this study.

The modified D&M IS Success Model's constructs of system quality, information quality, service quality, use, user satisfaction and net benefits were incorporated. Alongside the D&M IS Success Model was further modified in this study and several constructs were changed. System quality construct was changed to read “electronic health records (EHR)”, “Intention to use” was changed to reflect better coordination of patient care (BCP). In this study, the construct “net benefits” was altered to read “evidence-based healthcare practice (EBHP)”. While information quality and service quality were left unchanged, the D&M IS Success Model was expanded to include new constructs such as "medical error reduction (MER)" and "knowledge quality (KQ)." TAM was incorporated into the framework with two of its constructs, “perceived usefulness (PU)” and “perceived ease of use (PEU)” were included in the D&M IS Success Model.

However, TOE was included in the D&M IS Success Model to investigate the technological, organisational, and environmental factors that influence the adoption of EHR, which is the main driver in the adoption of EHBP. The model was then tested and validated, and the findings revealed that the adoption of EBHP is mostly driven by EHR, which has an impact on constructs such as MER, IQ, KQ, and the net benefit of these constructs leads to EBHP. It is clear from a thorough review of the literature that generally, little research has been conducted on the subject in South Africa. Furthermore, the conclusions and findings of this study will be a unique contribution to the knowledge base in the domains of health informatics and in particular, eHealth. In conclusion, one another significant contribution of this research to existing theory is the validation of the research model, using empirical data acquired at a South African public hospital.

6.3.2 Practical contributions of the conceptual framework

The study's findings highlight the need of improving patient health outcomes based on accurate patient diagnosis and treatment, which reduce hospitalisation in the setting of less developed countries. According to a study by Iroju et al. (2018), adopting EBHP is a challenging process that calls for both institutional changes and behavioural changes on the part of healthcare professionals. In addition, the findings of this study provide helpful suggestions for the effective adoption of EBHP in public hospitals. Findings also provide helpful guidance for successfully implementing EBHP in public hospitals in developing countries. The South African Pharmacy Council (SAPC), the National Department of Health in South Africa (NDoH), healthcare professionals, South African Universities, and research organisations, as well as the South African Nursing Council (SANC), can all benefit from this study because it outlines the advantages of EBHP adoption in public hospitals. Furthermore, according to de Gooyert, Rouwette, Van Kranenburg, and Freeman (2017), better decisions are made when a wide range of stakeholders are included.

In addition, to promote universal health quality goals and monitor and report quality of care results for continuous improvement efforts. The study claims that clinical guidance developed with the public interest in mind can help to improve treatment equality by enabling better services to be given to patients in need. Moreover, the results of this thesis contribute to the integration of the fragmented literature by generating new knowledge and supporting academics in comprehending how health professionals in South Africa and other developing countries view the usage of EHR. According to the findings of this study, healthcare professionals need a thorough understanding of the impact of EHR on IQ, KQ, MER, DTD and BCP for the South African public health sector to successfully adopt and implement EBHP. The main objective of using patient data exchange, according to Janakiraman et al. (2017) study, is to make it simpler for attending physicians to obtain patient information and to enable clinicians to retrieve that information when necessary. This will enable medical professionals to provide the patient with prompt, equitable, clear, effective, and efficient care. Conjointly, the final model of the study, which is depicted in Figure 6.1’s factors such as KQ, IQ, EHR, MER, when intermediated with

BCP as well as the DTD, have a significant impact on the adoption of EBHP in South African public hospitals. Hence the findings of the study revealed that the implementation of EHR system in South African public hospitals will provide a platform that enables patient medical records to be shared between provinces and, to provide a platform that allows patient medical records to be shared between provinces; that requires the implementation of an EHR system in South African public hospitals.

The model developed in this study will assist cash-strapped healthcare systems, in developing countries. Better patient care typically lowers health care costs. EBHP reduces the rate of unnecessary procedures and increases patient safety. For example, research-backed treatment approaches can reduce the number of patient falls, cases of ventilator-associated pneumonia and return visits all of which generate huge expenses. Along with reducing the number of incorrect diagnoses and other clinical errors, the more effective treatment that is provided as a result of EBHP can also shorten hospital stays. The application of EBHP will maximise the benefit to the patient by achieving optimum treatment outcomes while reducing cost and decreasing possible risks due to side effects and drug interactions. Furthermore, the goal of the healthcare patient information exchange (HIE) initiative is to improve access to relevant data so that decisions can be made with confidence. Prior to its acceptance, healthcare practitioners relied on patient feedback (Krousel-Wood *et al.,* 2018). Finally, the findings of this study provide new directions for further research.

6.3.3 Methodological contributions

The methodological contribution of the study is the use of a quantitative research approach and structural equation modelling (SEM) analysis to evaluate the critical success factors for the adoption of EBHP at a South African public hospital in Gauteng province. One of the study's most significant contributions is the structural model that was developed using SEM (see Figures 5.18 and 5.19). In this study, the conceptual framework was developed by combining the underlying theories of the TOE, TAM, and D&M IS Success Model. On the other hand, the study undertook a comprehensive statistical validation of the constructs adopted from these underpinning theories. In a sample of healthcare professionals from DGMAH, the relationship between these variables was thoroughly examined for validity and reliability and was shown to be well suited.

This study's methodology reflection was especially pertinent because it allowed for in-depth investigation and provided a variety of sources from which to draw data. Equally important, the relationship between the constructs in the proposed model was empirically investigated using SEM analysis, exploratory factor analysis (EFA) as well as confirmatory factor analysis (CFA). In general, the study's findings have offered solid support for the hypothesised relationships. These results could have an impact on South African public hospitals because they have been shown to be useful in evaluating the effects of EHR on various constructs such as IQ, KQ, MER, DTD and BCP. These variables may also be used by healthcare organisations as a basis of measurement for the adoption of EBHP. Further, the proposed conceptual model was developed based on the TOE, TAM, and D&M IS Success Model theories, and the hypothesised, hypotheses were tested using SEM. The findings of this study helped by providing ideas for fresh approaches that could also be used to fill this research methodological gap.

6.4 LIMITATIONS AND FUTURE RESEARCH

While this thesis contributes to the understanding of information systems (IS) success measurement factors, technology acceptance factors and organisational factors that promote EBHP adoption, it does have certain limitations. The key constraint in this study was the cross-sectional strategy, which could have a negative impact in this study. Although this method is a convenient, rapid, and low-cost way to gather data, it is not without flaws. Researchers have questioned cross-sectional studies due to bias, which happens when study participants do not accurately reflect the viewpoint of the general community, impacting research findings and the ability to generalise from them. This is because of the nature of the survey and the fact that respondents were only questioned once to complete the questionnaire (Sedgwick, 2014). Future research could look at long-term studies of these factors to address the shortfalls beyond the difficulty of cross-sectional studies.

A flaw in this study is that it relies on self-administered questionnaires, which could have skewed the results in a variety of ways. To begin with, social desirability inaccuracy is widespread in self-reported surveys. The survey respondents' perceptions of evidence-based healthcare practice may have been exaggerated, resulting in skewed participant response to the questionnaire survey. Furthermore, since there are hospitals and clinics that still use paper-based electronic record-keeping, most of the respondents were not very familiar with electronic health records. This could have influenced their responses to specific questions in the questionnaire, perhaps leading to less accurate results. In future, self-reporting and researcher bias can be avoided by making sure that answer alternatives do not lead the subject, framing questions correctly, providing suitable options, reviewing findings with peers and other safeguards.

In that case, research should be conducted to determine the critical success factors that influence the adoption of EBHP at a South African public hospital, with additional data collection strategies such as interviews and focus groups being used to determine which is the most viable. The COVID-19 restrictions laws that were implemented to prevent the spread of infection had a negative effect on data gathering at DGMAH. Instead of the anticipated 420 respondents, the study was only able to collect data from 300 due to the challenges encountered in gaining access to healthcare professionals.

The positivist paradigm was used to perform the research investigation. H8, H11, H13, and H15 were not evaluated and validated since the four variables (technical, environmental, organisational context, perceived usefulness, and service quality) were excluded as being unsuitable for further inquiry because their loading factors were less than 0.3. It would also be advantageous Since a positivist study research findinds can not be based on researcher’s personal viewpoint; more research should be done to test these hypotheses. However, it might be argued that the inclusion of these constructs would offer the results further context regarding how they effect the adoption of EBHP in public hospitals in South Africa and other developing countries.

In accordance with the original conceptual model in Figure 3.2, BCP is a mediating variable that intermediates between KQ, IQ, and EBHP, whereas DTD is a mediating variable that intermediates between EHR and EBHP. In Chapter 3 under sections vii and vi, as well as in Chapter 4 under 4.7.3, these mediating variables are covered. Future research ought to investigate further the mediating influences of these constructs since they were not tested in this study.

The current study only focused on one public hospital, future studies should investigate the perceptions and desires of both public and private hospitals as well as healthcare professionals, to quantify similar characteristics. Future research should focus on healthcare professionals' attitudes toward patients and the language used by patients and healthcare professionals to communicate. Hence, scope of this study, however, was limited to KQ, IQ, MER, BCP as well as DTD. Therefore, to expand the theoretical foundation of the EBHP framework, future studies may include some fresh and pertinent constructs such as trust, patient/physician confidentiality and doctor loyalty. In addition, the fact that this thesis was not able to test all the hypotheses is also a limitation. This could be because of the sample size or the lack of a comprehensive review and validation of the study on which the current thesis is based. More specifically, this viewpoint encourages pluralism in a validation inquiry by defining the validity of these constructs from a variety of worldviews (Jang, Wagner, & Park, 2016).

6.5 CONCLUSION

This study contained a cross-sectional survey to understand which critical success factors influence EBHP adoption at a South African public hospital. Three different theories, namely the updated and modified D&M IS Success Model, TAM and TOE formed the theoretical foundation of the study. While the D&M IS Success Model and TOE frameworks helped to understand the decision method for technology adoption and some aspects of implementation, TAM theory provided the usability factor from the individual user perspective. This study has shown EHR implementation in public hospitals as the driver for the adoption of EBHP. Nurses made up the majority of the participants (225). The results of the current study demonstrated that the adoption of EBHP is significantly influenced by HER which provides the platform of sharing patient medical records, x-rays, laboratory test results just to mention a few. In addition, EHR will provides the fundamental benefits by delivering "the right information at the right time in the right place" (Evans, 2018). This goal is accomplished by enhancing the patient records' conventional role as a repository for healthcare-related data. EHRs should help clinical decision making and should additionally direct the process of clinical issue solving (Naumann, Esdar, Ammenwerth, Baumberger & Hübner Ursula, 2019).

Literature has provided evidence that the implementation of EMR can improve the quality of medical care, yet a lack of financial incentives is regarded as a critical barrier to physicians adopting EMR. In this study, the construct EHR was found to have significant effects on KQ and IQ. The findings of this study indicate that EHR is crucial and the main construct influencing the adoption of evidence-based healthcare practices. It has further been shown that an EHR platform is highly essential in medical care decisions to achieve efficient care delivery within health facilities, reduces the risk of treatment errors, decreases patient waiting time, reduces medical errors, enhances timely communication among practitioners and enhances healthcare service delivery. The findings of this study indicated a positive relationship between the constructs: EHR with MER, IQ and KQ all showed a strong positive correlation toward the adoption of EBHP. According to the study's findings, developing evidence-based health policies (EBHP) is essential for putting those practises into practise. Through EBHPs, policies' efficacy, efficiency, accountability, and transparency are all enhanced. Additionally, cooperation between these communities must be promoted to make it easier for healthcare professionals, stakeholders, researchers, the department of health, and policymakers to communicate when working independently.

Better patient care coordination, diagnosis and treatment of diseases were linked to EBHP. In addition, the intended effect of EBHP is to standardise healthcare practices to reduce illogical variation in care, which is known to produce unpredictable health outcomes. Medical healthcare professionals must evaluate the effects of therapies on patients who are given the therapy and how they respond to the treatment because different treatments are likely to be used for distinct diseases and illnesses as well as variable treatment responses in different individuals. In addition, it is believed that sharing knowledge among healthcare professionals is essential for raising the standard of patient care. The sophisticated process of knowledge exchange, which can bridge cultural gaps and utilise more global language, also depends on understanding cultural influences. The creation of EBHPs may benefit from the open usage of data and networking that health information technology (HIT) may support.

Surprisingly, perceptions of ease of use had no impact on the adoption of EHRs in this study. Technical, environmental, organisational context, perceived usefulness, and service quality were the four variables that were eliminated because their loading factors were less than 0.3, and no further analyses were conducted on those constructs. It would be intriguing to empirically investigate how mediating variables affect the relationship where BCP is the mediating variable, intermediating between KQ, IQ, and EBHP, while DTD is the mediating variable, intermediating between EHR and EBHP. However, this investigation did not substantiate the associations that were hypothesised. The integrated framework of the current study lends itself to simple adjustment because of its generic approach to the investigation of the adoption of evidence-based healthcare practise in public hospitals in developing countries.

BIBLIOGRAPHY

Aarons, G.A., Ehrhart, M.G., Farahnak, L.R., & Sklar, M. (2018). Aligning leadership across systems and organisations to develop a strategic climate for evidence-based practice implementation. *Annu Rev Public Health*. 2014, 35: pp.255-274.

Abed, S. S. (2020). Social commerce adoption using TOE framework: An empirical investigation of Saudi Arabian SMEs. *International Journal of Information Management*, 53, pp.102-118.

Abekah-Nkrumah, G., Guerriero, M., & Purohit, P. (2014). ICTs and maternal healthcare utilisation. Evidence from Ghana. *International Journal of Social Economics*, 41(7), pp.518-541.

Abualrob, A. A., & Kang, J. (2016). The barriers that hinder the adoption of e-commerce by small businesses, Unique hindrance in Palestine. *Information Development,* 32(5): pp.1528–44.

Abubakar, F. M., & Ahmad, H. B. (2013). The moderating effect of technology awareness on the relationship between UTAUT constructs and behavioral intention to use technology: A conceptual paper. *Australian Journal of Business and Management Research*, *3*(2), pp.14-23.

Aburuz, M.E., Hayea, H.A., Al-Dweik, G., & Al-Akash, H.Y. (2017). Knowledge, Attitudes, and Practice about Evidence-Based Practice: A Jordanian Study. *Health Science Journal.* (11): pp.482–489. doi: 10.21767/1791-809X.1000489.

Acquah-Swanzy, M. (2015). *Evaluating Electronic Health Record Systems in Ghana: the case of Effia Nkwanta Regional Hospital.* Unpublished Thesis presented to the Arctic University of Norway.

Adane K, Muluye, D., & Abebe, M. (2013). Processing medical data: a systematic review. *Arch Public Health.* 71(1): pp.27.

Adeleke, I.T, Asiru, M.A. Oweghoro, B.M. Jimoh, A.B., & Ndana, A.M. (2014) Computer and internet use among tertiary healthcare providers and trainees in a Nigerian public hospital; *American Journal of Health Research,* 3(1-1), pp. 1-10.

Adenuga, K. I., Iahad, N. A., & Miskon, S. (2017). Towards reinforcing telemedicine adoption amongst clinicians in Nigeria. *International Journal of Medical Informatics*, 104, pp.84–96.

Adenuga, O., Kekwaletswe, R., & Coleman, A., (2015). eHealth integration and interoperability issues: towards a solution through enterprise architecture. *Health Information Science Systems,* 3(1), pp. 1-12.

Adewole, O. G., & Opele, J. K. (2019). Demographic change industry-specific innovation patterns in Nigeria: The implication for knowledge management practices. Noble *International Journal of Social Sciences Research*, 4(2), pp.25–32.

Adler-Milstein J, Holmgren, A.J, Kralovec, P, Worzala, C, Searcy T., & Patel, V. (2017). Electronic health record adoption in US hospitals: the emergence of a digital “advanced use” divide. *J Am Med Inform Assoc.* 2017;24(6): pp.1142–1148.

Afolaranmi. T. Hassan, I., Mbak, J., Luka, D., Audu, T., & Chirdan, O. (2018). Referral System: An Assessment of Primary Health Care Centres in Plateau State, North Central Nigeria ISSN:2455-3956, *World Journal of Research and Review (WJRR).* Volume-6, Issue-1, January 2018. pp. 82-86.

Ahmad, S. Z., Abu Bakar, A. R., Faziharudean, T. M., & Mohamad Zaki, K. A. (2015). An Empirical Study of Factors Affecting E-Commerce Adoption among Small- and Medium

Sized Enterprises in a Developing Country: Evidence from Malaysia. *Information Technology for Development,* 21(4), pp.555–572.

Ahmadi, H. Nilashi, M. Almaee, A, Soltani, M, Zare, M., & Sangar, A.B, et al. (2016). Multilevel model for the adoption of hospital information system: a case on Malaysia. J *Soft Comput Decis Support Syst*.;3(1): pp.61–74.

Ahmed, M. A., & van der Schaar, M. (2017). Bayesian inference of individualized treatment efects using multi-task gaussian processes. *NeurIPS.*

Akande, T. (2016): Referral system in Nigeria: Study of a tertiary health facility. *Ann Afr Med.* (3): pp.130-133.

Akbaş, U., Karabay, E., Yıldırım-Seheryeli, M., Ayaz, A., & Demir, Ö.O. (2019). Türkiye ölçme araçları dizininde yer alan açımlayıcı faktör analizi çalışmalarının paralel analiz sonuçları ile karşılaştırılması [*Comparison of exploratory factor analysis studies in Turkish measurement tools index according to parallel analysis results*]. Kuramsal Eğitimbilim Dergisi, 12(3), 1095-1123. Online]. https://doi.org/10.30831/akukeg.453786. [Accessed 16 September 2021].

Akhlaq, A., Sheikh, A., & Pagliari, C. (2017). Health information exchange as a complex and adaptive construct: scoping review. *Journal of Innovation in Health Informatics*, 23(4), pp. 633-683.

Akor, O., & John-Mensah, O. (2016). *Why Hospitals should Embrace Electronic Records* [Online]. Available: https://www.dailytrust.com.ng/news/health/why-hospitalsshould-embrace-electronic-medical-records/143001.html [Accessed 16 June 2020].

Akosile, A. & Olatokun, W., (2020). 'Factors influencing knowledge sharing among academics in Bowen University, Nigeria', *Journal of Librarianship and Information Science* 52(2), pp.410-427.

Akum, F. A. (2014). Health care financing in Ghana: health care providers, clients' perceptions and experiences in the Upper East Region of Ghana. J*ournal of Scientific Research and Studies*. Vol. 1(2), pp. 29-38.

Al Alawi, S, Al Dhaheri, A, Al Baloushi, D, Al Dhaheri, M., & Prinsloo, E.A. (2014). Physician user satisfaction with an electronic medical records system in primary healthcare centres in Al Ain: a qualitative study ', *BMJ Open*, vol. 4, no. 11, p. e005569.

Al-Abri, R., & Al-Balushi, A. (2014). Patient Satisfaction Survey As A Tool Towards Quality Improvement. *Oman Medical Journal*, 29(1), pp.3-7.

Alalwan, A. A., Baabdullah, A., Rana, N. P., Tamilmani, K., & Dwivedi, Y. K. (2018). Examining adoption of mobile internet in Saudi Arabia: Extending TAM with perceived enjoyment, innovativeness, and trust. *Technology in Society,* 55, pp.100–110.

Alalwan, A. A., Dwivedi, Y. K., & Rana, N. P. (2017). Factors influencing adoption of mobile banking by Jordanian bank customers: Extending UTAUT2 with trust. International *Journal of Information Management*, 37(3), pp.99-110.

Alam, S, S., Yunus, M., & Jani, M. (2011). An empirical study of factors affecting electronic commerce adoption among SMEs in Malaysia. *Journal of Business Economics and Management,* 12(2), pp.375–399.

Al-Aulamie, A. (2013). *Enhanced Technology Acceptance Model to Explain and Predict Learners' Behavioural Intentions in Learning Management Systems.* Doctoral Dissertation, University of Bedfordshire.

Aldredge, N. H., Rodriguez, D., González, J., & Burt, D. R. (2020). A Case Study of a Point-of-Care Electronic Medical Record [SABER] in Totonicapán, Guatemala: Benefits, Challenges, and Future Directions. *Annals of Global Health,* 86(1), pp.122.

Alhalhouli, Z.T., Hassan, Z., & Der, C. S., 2014. Factors affecting knowledge sharing behavior among stakeholders in Jordanian hospitals using social networks. *International Journal of Computer and Information Technology*,*3*(5), pp.919-928.

Al-Harbi, K. A. S. (2011). E-Learning in the Saudi tertiary education: Potential and challenges. *Applied Computing and Informatics*, 9(1), pp. 31–46.

Alharbi, S., & Drew, S. (2014). Using the technology acceptance model in understanding academics' behavioural intention to use learning management systems. International *Journal of Advanced Computer Science and Applications*, 5(1), pp.143-155.

Al-Hattami, H. M. (2021). Validation of the D&M IS success model in the context of accounting information system of the banking sector in the least developed countries. *Journal of Management Control*, pp.1-27.

AlKalbani, A., Deng, H., & Kam, B. (2015) "A Conceptual Framework for Information *Security in Public Organisations for E-Government Development,*" ACIS2014.

Allen, P., & Bennett, K. (2010). *PASW Statistics by SPSS: A Practical Guide: Version 18.0* (1st ed.). South Melbourne, Victoria, Australia: Cengage Learning Australia.

Alloghani, M., Hussain, A., Al-Jumeily, D., & Abuelma'atti, O. (2015). Technology Acceptance Model for the Use of M-Health Services among health-related users in UAE. *Paper presented at the 2015 International Conference on Developments of ESystems Engineering (DeSE).*

Al-Moosa, N.H., & Sharts-Hopko, N. (2016). Using change management to redesign oman's health professions education sector*. Health Professions Education*. Available at http://dx. doi.org/10.1016/j.hpe.2016.09.001. [Accessed 16 September 2021].

Al-Okaily, A., Abd Rahman, M. S., Al-Okaily, M., Ismail, W., N., S., W., & Ali, A. (2020). Measuring success of accounting information system: Applying the DeLone and McLean model at the organisational level. *Journal of Theoretical and Applied Information Technology,* 98(14), pp. 2697- 2706.

Alqahtani, A., Crowder, R., & Wills, G. (2017). Barriers to the Adoption of EHR Systems in the Kingdom of Saudi Arabia: An Exploratory Study Using a Systematic Literature Review. *Journal of Health Informatics in Developing Countries*, 11(2).

Altman, M., Huang, T.T.K. and Breland, J.Y. (2018). Design Thinking in Health Care. *Preventing Chronic Disease* 15, p. E117. doi: 10.5888/pcd15.180128.

Aminpour, Farzaneh, Farahnaz Sadoughi, & Maryam Ahamdi. (2016). "Utilisation Of Open-Source Electronic Health Record Around the World: A Systematic Review." *Journal Of Research In Medical Sciences* 19.1: pp.57-64.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin, 103*(3), pp.411–423.

Angeles, R. (2014). 'Using the technology-organisation-environment framework for analyzing Nike's "Considered Index" green initiative, a decision support system-driven system', *Journal of Management and Sustainability* 4(1), pp.96.

Anil Kumar Gupta, et al. (2017): Health system strengthening – focusing on referrals: an analysis from india. *Jupiter publishers, JOJ nurse health care.* 2(4).

Antwi, S.K., & Hamza, K. (2015). Qualitative and Quantitative Research Paradigms in Business Research: A Philosophical Reflection. *European Journal of Business and Management*, 7(3), pp.217-225.

Anyango, O. J. (2017). *Challenges to Electronic Medical Record Systems adoption: A Case of Coast Province General Hospital.*

Armitage, E. G., Godzien, J., Alonso-Herranz, V., López-Gonzálvez, Á., & Barbas, C. (2015). *Missing value imputation strategies for metabolomics data. Electrophoresis*, 36(24), pp.3050–3060.

Asan, O., Flynn, K. E., Azam, L., & Scanlon, M. C. (2017). Nurses' perceptions of a novel health information technology: a qualitative study in the pediatric intensive care unit. *International Journal of Human–Computer Interaction*, 33(4), pp.258-264.

Ash, J., S. Berg, M., Coiera, E. (2018). Some unintended consequences of information technology in health care: the nature of patient care information system-related errors. *J Am Med Inform Assoc*:11: pp.104–112.

Atasoy, H., Greenwood, B.N., & McCullough, J.S. (2019). The digitization of patient care: a review of the effects of electronic health records on health care quality and utilisation. *Annual review of public health*, 40, pp.487-500.

Auld, S., Kim, L., Webb, E., Podewils, L., & Uys, M. (2013). Completeness and concordance of TB and HIV surveillance systems for TB-HIV co-infected patients in South Africa. *The International Journal of Tuberculosis and Lung Disease* 17: pp.186–91.

Australian Institute of Health and Welfare. (2017). [Online] Available at: https://www.aihw.gov.au/reports/health-welfare-expenditure/health-expenditure-australia-2015-16/contents/dynamic-data [Accessed 16 May 2020].

Australians Health (2020). Data sets. (Australia Health series no. 17, Cat.No. AUS 231). *Australian Institution of Health and Welfare*. https://www.aihw.gov.au/reports/australias-health/australias-health-2020-data-insights/data. [Accessed on 15 June 2018].

Awa, H., Ukoha, O., & Emecheta, B. (2015). Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. *Journal of Science and Technology Policy Management,* 6(1), pp.76-94.

Awang, Z. (2012). Structural equation modeling using AMOS graphic. *Penerbit Universiti Teknologi MARA.*

Awogbami, P. A., Opele, J. K., & Chibueze, E. U. (2020). Lecturers' use of multimedia resources for knowledge transfer: A study of Adeleke University, Ede, Osun State. Information Impact, 11(2), pp.35–50.

Awol SM, et al. (2020). Health professionals' readiness and its associated factors to implement electronic medical record system in four selected primary hospitals in Ethiopia. *Adv Med Educ Pract*.;11(2): pp.147–62 10.2147%2FAMEP.S233368.

Ayabakan, S. Bardhan, I. Zheng, Z.Q., & Kirksey, K. (2017). The Impact of Health Information Sharing on Duplicate Testing. *MIS Quarterly.* ;41(4): pp.1083-1103.

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*, pp.112–122.

Bahadori, M. Alimohammadzadeh, K. Abdolkarimi, K., & Ravangard, R. (2017). Factors affecting physicians' attitudes towards the implementation of electronic health records using structural equation modeling (SEM) *Shiraz e-Medical Journal.* 16;18(11) doi: 10.5812/semj.13729.

Bailey, D., & Leonardi, P. (2015). *Technology Choices: Why Occupations Differ in Their Embrace of New Technology.* Cambridge, MA: MIT Press.

Baker, J. (2014). The technology–organisation–environment framework. In: Dwivedi YK, Wade MR, Schneberger SL, editors. *Information Systems Theory.* New York: Springer; 2014. pp. 231–45.

Balen, M. E., & Leyton, C. (2015). Policy translation: An invitation to revisit the work of Latour, Star and Marres. Global Discourse: *An Interdisciplinary Journal of Current Affairs and Applied Contemporary Thought.*

Ballaro, J. M., & Washington, E. R. (2016). The impact of organisational culture and perceived organisational support on successful use of electronic healthcare record (EHR). *Organisation Development Journal,* 34(2), pp11-29.

Bandalos, D. (2018). *Measurement theory and applications for the social sciences*. New York, NY: Guilford Press.

Banshanga, M., & Ejiri, A. H. (2016). Evaluating the adoption of Electronic Health Records (EHR) in referral Hospitals, Uganda. *International Journal of Scientific Knowledge,* 8(1), pp.1-5.

Bardhan, I. R., & Thouin, M. F. (2017). Health information technology and its impact on the quality and cost of healthcare delivery. *Decision Support System*, 55, pp. 438-449. doi: 10.1016/j.dss.2012.10.003.

Barkman, C., & Weinehall, L. (2017). Policymakers and mhealth: Roles and expectations, with observations from Ethiopia, Ghana, and Sweden. *Global health action*, 10(sup3):1337356.

Barnett, J.C., & Berchick, E.R. (2016). Health insurance coverage in the United States: 2016. Washington, DC: U.S. Government Printing Office. *Current population report no.* pp.60-260.

Barrett, P. (2007). Structural equation modelling. *Adjudging model fit. Personality and Individual Differences.* 42(5): pp.815–824.

Batalden, P., Davidoff, F., Marshall, M., Bibby, J., & Pink, C. (2011). So what? Now what? Exploring, understanding, and using the epistemologies that inform the improvement of healthcare. *BMJ Quality & Safety*, 20(1), pp. 99-105. doi:10.1136/bmjqs.2011.051698.

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*, pp.15–22.

Beckers Health IT. (2016). *Unpacking hospitals' EHR implementation costs: what's behind the million-dollar price tags*? URL:https://www.beckershospitalreview.com/healthcare-information-technology/unpacking-hospitals-ehr-implementation-costs-what-s-behind-the-million-dollar-price-tags.html[Accessed 16 June 2020].

Bedeley, R., & Palvia, P. (2018). A study of the issues of E-health care in developing countries: The case of Ghana*. In Proceedings of the Twentieth Americas Conference on Information Systems. Savannah,* GA.

Behera, M., R, Behera D, & Satpathy, S., K. (2020). Planetary health and the role of community health workers. *Journal of Family Medicine and Primary Care.* 9(7): p. 3183.

Beigmoradi, S., Pourshirvani, A., Pazokian, M., & Nasiri, M. (2019). Evaluation of nursing using situation-background-assessment-recommendation checklist in general wards. *Evidence Based Care Journa*l, 9(3), pp.63-68.

Belay, M., Desta, A., Smithson, S. & Meshesha, M., (2021). 'Alignment of knowledge management process with clinical process to support evidence-based decision in healthcare improvements: The case of selected Ethiopian hospitals', *Knowledge and Process Management*, 28(1), pp. 3-10.

Bell, E., Bryman, A. & Harley, B. (2018). *Business research methods,* 5th Edition, Oxford: Oxford university press.

Bello, U. L., Hassan, L., Yunusa, U., Abdulrashid, I., Usman, R. H., & Nasidi, K. N. (2017). Challenges of information and communication technology utilisation among undergraduate community health nursing students in Tanta University, Egypt. *American Journal of Nursing,* 6(3), pp.274–279.

Ben-Assuli, O. (2015). Electronic health records, adoption, quality of care, legal and privacy issues and their implementation in emergency departments. *Health Policy*, 119, pp. 287–297. doi: 10.1016/j.healthpol.11.014.

Benesty, J., Chen, J., Huang, Y., & Cohen, I. (2009). Pearson correlation coefficient. In *Noise reduction in speech processing.* pp. 37–40. Springer.

Berghout, M. Fabbicoth, I. Buljac, M. Carina, A., & Hilders, J.M. (2017). Medical leaders or master: *A systematic review of medical leadership in hospital settings.* PLOS/ONE.

Bhattacharyya, S.C., & Palit, D. (2016). Mini-grid based off-grid electrification to enhance electricity access in developing countries: What policies may be required? *Energy Policy*. 94: pp.166–178. 10.1016/j.enpol.2016.04.010.

Bhattacherjee, A. (2012). Social Science Research: Principles, Methods, and Practices. *Open University Press, USF Tampa Bay*.

Bienkowska-Gibbs, T., King, S., Saunders, C. L., & Henham, M. L. (2015). New organisational models of primary care to meet the future needs of the NHS. *A brief overview of recent reports.* Retrieved from RAND Europe, Cambridge, website: https://www.rand.org/content/dam/rand/pubs/research_reports/RR1100/RR1181/RAND_RR1181.pdf. [Accessed 16 June 2020].

Björnberg, A., (2017). Euro Health Consumer Index [Online] Health consumer powerhouse. [Online]. Available at: https://healthpowerhouse.com/media/EHCI-2017/EHCI-2017-report.pdf [Accessed 16 June 2020].

Blumenthal, S. (2018). Improving interoperability between registries and ehrs. *AMIA Summits on Translational Science Proceedings,* 2017, pp.20.

Bodroža, B., & Jovanović, T. (2016). Validation of the new scale for measuring behaviors of Facebook users: Psycho-social aspects of Facebook use (PSAFU). *Computers in Human Behavior,* 54, pp.425-435.

Bolonne, H., & Wijewardene, P. (2020). Critical success factors Affecting the Intention to Adopt Big Data Analytics in Apparel Sector, Sri Lanka. *Int. J. Adv. Comput. Sci. Appl.* pp.*11*.

Bonnet, D. G., & Wright, T.A. (2015). Cronbach‟s alpha reliability: Interval estimation, hypothesis testing, and sample size planning. *Journal of Organisational behaviour.* (36). pp. 3 – 15.

Boomsma, A. (1983). *On the robustness Of LISREL (Maximum Likelihood Estimation) against small sample size and non-normality.* Unpublished Ph.D. Dissertation, Groningen, University of Groningen.

Borgman, H. P., Bahli, B., Heier, H., & Schewski, F. (2013). 'Cloudrise: Exploring Cloud Computing Adoption and Governance with the TOE Framework'. *System Sciences (HICSS), 46th Hawaii International Conference* on, pp. 4425–4435.

Boru, T. (2018). *Chapter Five Research Design and Methodology* 5.1 Introduction, DOI: 10.13140/RG.2.2.21467.62242.

Borycki, E., Courtney, K. & Kuo, A. (2017) (Editors). Building capacity for health informatics in the future: *Studies in health technology and informatics.* 234. Amsterdam: IOS Press BV.

Bossen C, Jensen LG, Udsen FW. (2016) Evaluation of a comprehensive EHR based on the DeLone and McLean model for IS success: approach, results, and success factors. *Int J Med Inform;* 3; 82(10): pp. 940-53.

Brandl, B., & Hornuf, L. (2020). Where did FinTechs come from, and where do they go? The transformation of the financial industry in Germany after digitalization. *Frontiers in Artificial Intelligence, 3,* pp*. 8.*

Brandon-Jones, A., & Kauppi, K. (2018). "Examining the antecedents of the technology acceptance model within e-procurement", *International Journal of Operations & Production Management*, 38 (1), pp. 22-42.

Brannen, J. (2017). *Mixing methods: Qualitative and quantitative research.* London: Routledge.

Brom, C., Lukavský, J., Greger, D., Hannemann, T., Straková, J., & Švaříček, R. (2020). *Mandatory home education during the COVID-19 lockdown in the Czech Republic: A rapid survey of 1st-9th graders' parents.* Frontiers in Education, 5(103). doi:10.3389/feduc.2020.00103.

Brown, T. A. (2015). *Confirmatory Factor Analysis for Applied Research* (2nd Edition). New York, NY: Guilford Publications.

Bruce, N., Pope, D., & Stanistreet, D. (2018). *Quantitative methods for health research: a practical interactive guide to epidemiology and statistics.* (2nd Edition). Hoboken: Wiley.

Bryman, A., & Bell, E. (2015), *Business Research Methods,* Oxford University Press, Oxford.

Burger, R., & Christian, C. (2018). Access to Health Care in Post-Apartheid South Africa: Availability, Affordability, Acceptability. Health Economics, Policy and Law, 15(1), pp. 43-55. Available at https://DOI.org/10.1017/S1744133118000300. [Accessed 16 September 2021].

Burlacu, D., & Roescu, A. (2021), "Chapter 3. Public Opinion on Healthcare," in E. M. Immergut, K. M. Andersen, C. Devitt and T. Popic (eds), *Health Politics in Europe: A Handbook*. Oxford University Press, pp. 49–68.

Byrne, B. M. (2016). *Structural equation modelling with AMOS: basic concepts, applications, and programming*, (3rd Edition). New York: Routledge.

Camargo, F., C, Iwamoto, H., H, Galvão, C., M. (2018). Models for the implementation of evidence-based practice in hospital-based nursing: A narrative review1. *Texto & Contexto-Enfermagem.* 26.

Campanella, P., Lovato, E, Marone, C, Fallacara, L. Mancuso, A., & Ricciardi W. (2016). The impact of electronic health records on healthcare quality: A systematic review and meta-analysis. *Eur J Public Health*.pp.26. pp. 60-64.

Cao, Q., Jones, D. R., & Sheng, H. (2014). Contained nomadic information environments: Technology, organisation, and environment influences on adoption of hospital RFID patient tracking. *Information & Management*, 51(2), pp. 225-239.

Capurro, D. Yetisgen M., & van Eaton, E. (2014). Availability of structured and unstructured clinical data for comparative effectiveness research and quality improvement: a multisite assessment. *EGEMS (Wash DC).*2: 1079.

Cardoso, L., Marins, F., Portela, F., Santos, M., Abelha, A., & Machado, J. (2014). The Next Generation of Interoperability Agents in Healthcare. *International journal of environmental research and public health,* 11(5), pp. 5349-5371.

Cattell, R. B. (1966). The meaning and strategic use of factor analysis. In R. B. Cattell (Ed.), *Handbook of multivariate experimental psychology,* pp. 174-243. Chicago: Rand McNally.

Cavazza, M., Del Vecchio, M., Fattore, G. & Fenech, L. (2023). "Geographical Variation in the Use of Private Health Insurance in a Predominantly Publicly Funded System," *Health Policy*. / (Socialstyrelsen, 2016).

Cebul, R. D., Love, T. E., Jain, A. K., & Hebert, C. J. (2011). Electronic health records and quality of diabetes care ', *New England Journal of Medicine*, 365(9), pp. 825–833.

Çetin, S., Ergün, M. A., Tekindal, M. A., Tekindal, B., & Tekindal, M. (2015). A qualitative evaluation of the knowledge levels of nurses regarding informatics and health informatics: The case of Atatürk training and research hospital. *International Journal of Caring Sciences,* 8(3), pp.555–565.

Chakravorty, T., Jha, K., & Barthwal, S. (2019). Linking EHR and ERP in Healthcare Operations: A Conceptual Note. *The IUP Journal of Operation Management,* XVIII (2).

Chang, C. T., Hajiyev, J., & Su, C. R. (2017). Examining the students' behavioral intention to use elearning in Azerbaijan? The general extended technology acceptance model for e-learning approach. *Computers & Education,* 111, pp.128-143.

Chang, H. H., & Chen, S. W. (2016). Consumer perception of interface quality, security, and loyalty in electronic commerce. Information and management, 46(7), pp. 411-417.

Channoi, R., Clemes, M., & Dean, D. (2018). A comprehensive hierarchical model of beach resort hotel stays. *Journal of Hospitality and Tourism Management*, 37, pp. 107-116.

Chao, W.C. Hu, H. Ung, C.O.L., & Cai, Y. (2013). Benefits and Challenges of Electronic Health Record System on Stakeholders: A Qualitative Study of Outpatient Physicians; *Journal of Medical Systems;* 37:9960.

Chara, M. (2011). Course 7 Unit 1 – *Introduction & Overview: Components of HIT Systems.* [Online] Available at: https://www.slideshare.net/MegasChara/course-7-unit-1-introduction-overviewcomponents-of-hit-systems [Accessed 15 03 2019].

Chase, D, A, Ash, J., S, Cohen, D., J, Hall, J, Olson, G., M, & Dor, D., A. (2017). The EHR's roles in collaboration between providers: a qualitative study. *In: AMIA Annual symposium proceedings archive.* pp. 1718–27.

Chatterjee, Sheshadri, Nripendra, P. Rana, Yogesh, K. Dwivedi, & Abdullah M. Baabdullah. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change* 170: 120880.

Chau, Ngoc, Tuan, Hepu Deng, & Richard, Tay. (2020). Critical determinants for mobile commerce adoption in Vietnamese small and medium-sized enterprises. *Journal of Marketing Management* 36: pp. 456–87.

Chen, F.F. Sousa, K.H., & West, S.G. (2005). *Testing Measurement Invariance of Second-Order Factor Models. Structural Equation Mo*deling, 12: pp. 471-492.

Chen, J. Q., & Benusa, A. (2017). HIPAA security compliance challenges: The case for small healthcare providers. *International Journal of Healthcare Management,* 10(2), pp.135-146.

Chen, Y. J, Chindarkar, N., & Xiao, Y. (2019). Effect of reliable electricity on health facilities, health information, and child and maternal health services utilisation: evidence from rural Gujarat, India. *Journal of Health, Population and Nutrition.* 38(1): 7 10.1186/s41043-019-0164-6.

Cheung, G. W., & Rensvold, R., B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural Equation Modeling.*2002(9), pp. 233–255.

Cheung, K. C., van der Veen, W., Bouvy, M.L., Wensing, M., van den Bemt, P. M., & de Smet, P. A. (2014). Classification of medication incidents associated with information technology. *J Am Med Inform Assoc.* 21(e1), pp. 63–67.

Cho, KW, Bae, S., K, Ryu, J.H, Kim, K., N, An, C.vH, & Chae, Y., M. (2015). Performance evaluation of public hospital information systems by the information system success model. Healthc Inform Res. 21(1), pp. 43-48.

Chow, M., Herold, D. K., Choo, T. M., & Chan, K. (2012). Extending the technology acceptance model to explore the intention to use second life for enhancing healthcare education. *Computers & Education*, 59(4), pp. 1136–1144.

Chowles, T. (2014). *Western Cape Leads the Continent with PHCIS* – E-health News ZA. [Online] e-Health News ZA. Available at: [Accessed 17 April 2020].

Christensen, A. I., Ekholm, O., Glümer, C., & Juel, K. (2014). Effect of survey mode on response patterns: comparison of face-to-face and self-administered modes in health surveys. *The European Journal of Public Health*, 24(2), pp. 327–332.

Christine, T., Adedapo, O., Jun, C., & Ramayah, T. (2019). Measuring the Influence of Service Quality on Patient Satisfaction in Malaysia, *Quality Management Journal.* 26(3), pp. 129-143.

Creswell, J. W. & Guetterman (2019). *Educational research: Planning, conducting, and evaluating quantitative and qualitative research* (6 th ed). Upper Saddle, NJ: Pearson.

Chukmaitov, A. S., Harless, D. W., Bazzoli, G. J., & Deng, Y. (2017). Factors associated with hospital participation in Centers for Medicare and Medicaid Services' accountable care organisation programs. *Health Care Management Review*. Advance online publication. Doi: 10.1097/HMR.0000000000000182.

Clemes, M. D., Dean, D. L., & Thitiya, T. (2020). Modelling the Behavioral Intentions of Day Spa Customer. *Asia Pacific Journal of Marketing and Logistics*, 32(8), pp.1699-1716.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple 520 correlation/regression analysis for the behavioral sciences* (Lawrence Earlbaum 521 Associates). Hillsdale, NJ.

Cohen, J. K. (2017). *EHR implementations with the biggest price tags in 2017. Becker's Health IT.* https://www. beckershospitalreview.com/ehrs/10-ehr-implementations-with-the-biggest-price-tags-in-2017. html[Accessed 14 July 2020].

Çokluk, Ö., Şekercioğlu, G., & Büyüköztürk, Ş. (2012). Sosyal bilimler için çok değişkenli istatistik SPSS ve LİSREL uygulamaları [*Multivariate statistics for social sciences: SPSS and LISREL applications]* (2. Baskı). Pegem Akademi.

Cole, M. A. Elliott, R. J., & Strobl, E. (2014). *Climate change, hydrodependency, and the African Dam boom World Dev.* 60 pp. 84–98.

Colicchio, T. K., Cimino, J. J., & Del Fiol, G. (2019). Unintended consequences of Nationwide electronic health record adoption: challenges and opportunities in the post-meaningful use era. *J Med Internet Res*. 2019; 21(6): e13313.

Collier R. (2018). *Rethinking EHR interfaces to reduce click fatigue and physician burnout. CMAJ.*190(33).

Colombo, F., Oderkirk, J., & Slawomirski, L. (2020). Health Information Systems, Electronic Medical Records, and Big Data in Global Healthcare: Progress and Challenges in OECD Countries, in: Haring, R., Kickbusch, I., Ganten, D., Moeti, M. (Eds.), *Handbook of Global Health*. Springer International Publishing, Cham, pp. 1–31. https://doi.org/10.1007/978-3-030-05325-3_71-1. [Accessed 16 September 2019].

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. *Lancet.* 374: pp.817–34.

Costanzo, A.; & Desimoni, M. (2017). Beyond the Mean Estimate: A Quantile Regression Analysis of Inequalities in Educational Outcomes Using INVALSI Survey Data*. Large-Scale Assess.* Educ. 5, 14.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: qualitative, quantitative, and mixed methods approachs.* (5th Edition). Thousand Oaks, California, SAGE Publications, Inc.

Croasmun, J.T., & Ostrom, L. (2016). *Using Likert-Type Scales in the Social Sciences. Journal of Adult Education*, 40: pp. 19-22.

Cronbach, L. (1951). *Coefficient alpha and the internal structure of tests. Psycho- metri*ka. 16: pp. 297–334.

Cruz-Jesus, F., Pinheiro, A., & Oliveira, T. (2019). Understanding CRM adoption stages: Empirical analysis building on the TOE framework. *Comput. Ind.* 109, pp. 1–13.

Da Costa, C., & Schneider, Z. (2018). *Quantitative data collection and study validity. In Nursing and Midwifery Research*, (5th Edition). Schneider, Z., Whitehead, D., LoBiondo-Wood, G., Haber, J., Eds.; Elsevier Australia: Chatswood, NSW, Australia, pp. 181–196.

Da Silva, B. A., & Krishnamurthy, M. (2016). The alarming reality of medication error: A patient case and review of Pennsylvania and national data. *Journal of Community Hospital Intern Medical Perspective,* 6(4), pp.1-6.

Da-Costa Vroom, F. B., Godia, A., Derya, S., & Afagbedzi, S. (2017). Perceptions of EMR usage by health sciences students in Ghana. *Journal of Health Information in Africa,* 4(1), pp.58-67.

Damnjanovic, V., Jednak, S., & Mijatovic, I. (2015). *Factors affecting the effectiveness and use of Moodle: students' perception. Interactive Learning Environments*, 23(4), pp. 496–514.

Daniel, B. K., & Harland, T. (2017). *Higher education research methodology: A step-by-step guide to the research process.* Routledge.

David, G. C., Chand, D., & Sankaranarayanan, B. (2014). Error rates in physician dictation: Quality assurance and medical record production. *International Journal of Health Care Quality Assurance,* 27, pp. 99-110. doi:10.1108/JHCQA-06-2012- 0056.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), pp. 319–339.

Davis, K., Stremikis, K., Squires, D., & Schoen, C. (2014). Mirror, mirror on the wall, 2014 update: How the U.S. Health care system compares internationally. *The Commonwealth Fund*. [Online]. Available at: http://www.commonwealthfund.org/publications/fund-reports/2014/jun/mirror-mirror. [Accessed 16 September 2021].

De Carvalho J., & Chima, F.O. (2014). Applications of structural equation modelling in social sciences research. *American International Journal of Contemporary Research.* 2014, 4(1), pp. 6–11.

de Gooyert, V., Rouwette, E., van Kranenburg, H., & Freeman, E. (2017). Reviewing the role of stakeholders in Operational Research; A stakeholder theory perspective. *European Journal of Operational Research.*

De Pietro, C., & Francetic, I. (2018). E-health in Switzerland: the laborious adoption of the federal law on electronic health records (EHR) and health information exchange (HIE) networks. *Health Policy* 122(2), pp. 69–74.

DeLone W. H., & McLean, E. R. (1992). “Information systems success: the quest for the dependent variable,” *Information Systems Research,* 3(1), pp. 60–95.

DeLone, W. H., & McLean, E. R. (2003). The Delone and Mclean model of information systems success: A ten-year update. *Journal of Management Information Systems,* 19(4), pp. 9–30.

DeLone, W. H., & McLean, E. R. (2016). "Information Systems Success Measurement", *Foundations and Trends® in Information Systems:* 2(1), pp 1-116.

Denscombe, M. (2014). *The Good Research Guide*, Maidenhead: Open University Press.

Deokar, A. V., & Sarnikar S. (2016). Understanding Process Change Management in Electronic Health Record Implementations. *Inf. Sys. E-Bus. Manag.*; pp.14:733–766. doi: 10.1007/s10257-014-0250-7.

Department of Health & CSIR. (2016). '*National Health Normative Standards Framework for Interoperability in eHealth in South Africa'*, Standard, 240075.

Department of Health & Human Services. (2014). Medicare and Medicaid Programs; Electronic Health Record Incentive Program. Final rule. *Fed Regist*; 75144: pp. 44314–588.

Department of Health. (2014). '*Development of eHealth strategy for South Africa', report delivered at WHO–ITU meeting National eHealth strategy development: Country experience and next steps,* Geneva, Switzerland, 24–26 July 2012.

Dessie, G. (2017). Knowledge Sharing Practice and Associated Factors Among HealthCare Workers at Public Hospitals in North Shoa, Amhara. *American Journal of Health Research*, *5*(5), p.149.

Devasenapathy, N., Jerath, S. G., Sharma, S., Allen, E., Shankar, A. H., & Zodpey, S. (2016). Determinants of childhood immunisation coverage in urban poor settlements of Delhi, India: a cross-sectional study. *BMJ Open.*

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organisational measure development: a comparison and empirical illustration. *British Journal of Management;* 17(4), pp. 263-282.

DigiData (Pty) Ltd. 2017. *Pro-Clin.* [Online]. Available at: http://www.digidata.co.za/proclin.html. [Accessed 19 December 2021].

Dion, Paul, A. (2008). Interpreting Structural Equation Modeling Results: A Reply to Martinand Cullen. *Journal of Business Ethics,* 83, pp.365 – 368.

Dixon, B. E., Grannis, S. J., McAndrews, C., Broyles, A. A., Mikels-Carrasco, W., Wiensch, A., Williams, J. L., Tachinardi, U., & Embi, P.J. (2021). Leveraging data visualization and a statewide health information exchange to support COVID-19 surveillance and response: Application of public health informatics. *Journal of the American Medical Informatics Association ocab004.* [Online]. Available at: https://doi.org/10.1093/jamia/ocab004. [Accessed 16 September 2021].

Djulbegovic, B., & Guyatt, G. H. (2017). Progress in evidence-based medicine: a quarter century on. *The Lancet,* 390(10092), pp. 415-423.

Doberne, J. W., Kakaday, R., Redd, T. K., Ericksson, C. O., Yackel, T. R., Marquard, J., & Chiang, M. F. (2015). Barriers to information access in electronic health records during initial patient visits: A qualitative study. *Proceedings of the International Symposium on Human Factors and Ergonomics in Healthcare*, 4, pp. 143-149. doi:10.1177/2327857915041009.

Dong, S., Xu, S. X., & Zhu, K. X. (2016). Research note—information technology in supply chains: The value of it-enabled resources under competition. Information systems research, 20(1), pp. 18-32.

Drisko, J. W., & Grady, M. D. (2019). *Evidence-based practice in clinical social work. (*2nd Edition). Springer.

Dubovitskaya, A., Xu, Z., Ryu, S., Schumacher, M., & Wang, F. (2017). Secure and Trustable Electronic Medical Records Sharing Using Block-Chain. *AMIA Annual Symposium Proceedings*, August, pp. 650–659.

Duckett, S. Coming Out of COVID-19 Lockdown: The Next Steps for Australian Health Care. Grattan Institute (2020). [Online]. Available at: https://grattan.edu.au/report/coming-out-of-covid/ [Accessed 16 September 2021].

Dudding, K. M., Gephart, S. M., & Carrington, J. M. (2018). Neonatal nurses experience unintended consequences and risks to patient safety with electronic health records. *Computers, Informatics, Nursing*, 36(4), pp. 167–176.

Dunjwa, M. (2016). *Public health facilities audit results: Office of Health Standards Compliance (OHSC) briefing*, Parliamentary Monitoring group, Pretoria, South Africa.

Dutta, A., Krishnan, D., Ramanathan, S., Roy, R., Seetharaman, P. & Veppathur Mohan, R. (2015). EMR adoption: a user perception study in T*wenty-first Americas Conference on Information Systems, Puerto Rico* (August 13 – August 15, 2015), August, pp. 1- 13.

Eboreime, E., Bozzani, F., & Abimbola, S. (2015). Access to routine immunization: a comparative analysis of supply-side disparities between Northern and Southern Nigeria. PLoS ONE. 10(12): e0144876.

e-Health News. (2014). *Report: eHealth Strategy South Africa 2012-2017.* [Online]https://health-e.org.za/2014/09/11/report-ehealth-strategy-south-africa-2012. [Accessed 16 March 2019].

El Mahalli, A. E. (2015). Adoption and barriers to adoption of electronic health records by nurses in three governmental hospitals in Eastern Province, Saudi Arabia ‘, *Perspectives in Health Information Management,* 12, pp. 1-16.

Elfil, M., & Negida, A. (2017). Sampling methods in clinical research; an educational review. *Emergency*, 5(1), pp. 1-5.

El-Gayar, O., & Timsina, P. (2014). *Opportunities for business intelligence and bigdata analytics in evidence-based medicine.* Paper presented at the pp. 749-757.doi:10.1109/HICSS.2014.100.

Elkaseh, A. M., Wong, K. W., & Fung, C. C. (2015). The Acceptance of e-learning as a tool for teaching and learning in Libyan higher education. *IPASJ International Journal of Information Technology (IIJIT),* 3(4), pp. 1–11.

Emad, H., El-Bakry, H. M., & Asem, A. (2016). A modified technology acceptance model for health informatics. *International Journal of Artificial Intelligence and Mechatronics,* 4(4): pp. 153–161.

Emparanza, J. I., Cabello, J. B., & Burls, A. J. (2015). Does evidence-based practice improve patient outcomes? An analysis of a natural experiment in a Spanish hospital. *Journal of Evaluation in Clinical Practice,* 21(6), pp. 1059-1065.

Erasmus, L. E., & Van der Walt, T. (2015). Electronic medical records system user acceptance. *Proceedings of the IAMOT Conference 2015.* pp. 8–11 June 2015.

Esen, M., & Ozbag, G. K. (2016). An investigation of the effects of organisational readiness on technology acceptance in e-HRM applications. *International Journal of Human Resource Studies, 4*(1), p. 232.

Essén, A., Scandurra, I., Gerrits, R., Humphrey, G., Johansen, M. A., Kiergegaard, P., & Ancker, J. S. (2018). Patient access to electronic health records: Differences across ten countries. *Health Policy and Technology,* 7(1), pp.44-56.

Ethniks. (2013). *About Delta 9*. [Online]. Available at: http://www.delta9.co.za/. [Accessed 16 September 2021].

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics*, 5(1), pp. 1-4.

Evans, R. S. (2018). Electronic health records: then, now, and in the future. *Yearb Med Inform.* 2018 Mar 06; 25(S 01), pp. S48–S61. doi: 10.15265/iys-2016-s006.

Faber, M. J., Grande, S., Wollersheim, H., Hermens, R., & Elwyn, G. (2014). Narrowing the gap between organisational demands and the quest for patient involvement: The case for coordinated care pathways. *International Journal of Care Coordination,* (17), pp. 72-78.

Fabrigar, L. R., & Wegener, D. T. (2012). *Understanding statistics: Exploratory factor analysis.* New York, NY: Oxford University.

Falchetta, G., Gernaat, D., Hunt, J., & Sterl, S. (2019). Hydropower dependency and climate change in sub-Saharan Africa: a nexus framework and evidence-based reviewJ*. Clean. Prod.* (231), pp. 1399–417.

Fanta, G. B., Pretorius, L., & Erasmus, L., D. (2015). An evaluation of eHealth systems implementation frameworks for sustainability in resource constrained environments: a literature review. *In: IAMOT 2015 Conference Proceedings*, Cape Town Google Scholar.

Faustino, P., & Simões, D. (2020). The Contribution of the Technology Acceptance Model for an Active Teaching and Learning Process in Higher Education: A Bibliometric Analysis. *In Handbook of Research on Digital Learning*. pp. 242-261. IGI Global.

Field, A. (2016). *Discovering Statistics using SPSS*, (4th Edition). London: SAGE.

Finset, A. (2018). Among the topics of this issue: Health literacy and interpreter mediated communication. *Patient Education and Counselling,* 101(1), p.1.

Fisk, M., Livingstone, A., & Pit, S. W. (2020). *Telehealth in the context of COVID-19: Changing perspectives in Australia, the United Kingdom, and the United States* (Preprint). doi:10.2196/preprints.19264.

Flieger, S. P. (2017). Implementing the patient-centered medical home in complex adaptive systems: Becoming a relationship-centered patient-centered medical home. *Health Care Management Review,* 42, pp.112-121.

Florczak, K, L. (2017). Evidence or Clinicians or the Person: Who Should Be at the Center? *Nurs Sci Q.* 30(1): 17–20.

Ford, E. W., Silvera, G. A., Kazley, A. S., Diana, M. L., & Huerta, T. R. (2016). Assessing the relationship between patient safety culture and EHR strategy. *International Journal of Health Care Quality Assurance,* 29, pp. 614-627.

Fornell, C., & Cha, J. (1994). "Partial least squares", in Bagozzi, R. (Ed.), *Advanced Methods of Marketing Research, Blackwell*, Oxford, pp. 52-78.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), pp. 39–50.

Foschi, M. (2014). Hypotheses, operationalizations, and manipulation checks. In Laboratory experiments in the social sciences. pp. 247-268. *Academic Press.*

Fragidis, L. L., & Chatzoglou, P. D. (2018). Implementation of a nationwide electronic health record (EHR): The international experience in 13 countries. *International Journal of Health Care Quality Assurance,* 31, pp. 116-130.

Freedman, D. (2009). *Statistical Models: Theory and Practice*. Revised Edition, Cambridge University Press.

Furukawa, M., F, King, J, Patel V, Hsiao, C., J, Adler-Milstein, J., & Jha A. K. (2014). Despite substantial progress in EHR adoption, health information exchange and patient engagement remain low in office settings. *Health Aff*; 339: pp. 1672–1679.

Furusa, S. S., & Coleman, A. (2018). Factors influencing eHealth implementation by medical doctors in public hospitals in Zimbabwe. South African *Journal of Information Management,* 20(1), pp. 1-9.

Gagnon, M. P., Nsangou, E. R., Payne-Gagnon, J., Grenier, S., & Sicotte, C. (2014). Barriers and facilitators to implementing electronic prescription: a systematic review of user groups' perceptions*. J Am Med Inform Assoc*. (3): pp. 535–41.

Gagnon, M. P., Simonyan, D., Godin, G., Labrecque, M., Ouimet, M., & Rousseau, M. (2016). Factors influencing electronic health record adoption by physicians: A multilevel analysis. *International Journal of Information Management*, 36(3), pp. 258- 270.

Gartlehner, G., & Matyas, N. (2016). *How contextual issues can distort shared decision making.* Zeitschrift für Evidenz, Fortbildung und Qualität im Gesundheitswesen, 118, pp. 17-23.

Gaskin, C. J., & Happell, B. (2013). On exploratory factor analysis: A review of recent evidence, an assessment of current practice, and recommendations for future use. *International Journal of Nursing Studies.*

Gaskin, J., E. (2017). Confirmatory factor analysis: Validity and reliability. [Online]. Available at: http://statwiki.kolobkreations.com/index.php?title=Confirmatory_Factor_Analysis. [Accessed 16 September 2021].

Gharaibeh, M. K., & Gharaibeh, N. K. (2020). An empirical study on factors influencing the intention to use mobile learning. *Advances in Science, Technology and Engineering Systems Journal.* 5(5), pp. 1261-1265.

García-Vera, M., Merighi M. A. B., Conz, C. A., Silva, M. H., Jesus, M. C. P., & Muñoz-González, L. A. (2018). *Primary Health Care: The experience of nurses. Rev Bras Enferm. 71(Suppl 1), pp. 531-537.*

Gijsenberg, M., Van Heerde, H. J., & Verhoef, P. C. (2015). Losses loom longer than gains: Modeling the impact of service crises on perceived service quality over time. *Journal of Marketing Research*, *52*(5), pp. 642–656.

Gordon, J. E., Leiman, J. M., Deland, E. L., & Pardes, H. (2014). Delivering value: provider efforts to improve the quality and reduce the cost of health care. *Annu Rev Med*. 2014(65), pp. 447–458.

Gqirana, T. (2015). *NHI to reduce cost of healthcare.* [Online]. Available at: https://www.mg.co.za/article/2015-08-22-nhi-to-reduce-cost-of-healthcare/. [Accessed 16 September 2021].

Gravetter, F. J., & Forzano, L. B. (2012). *Research Methods for the Behavioral Sciences* (4th Edition). Belmont, CA: Wadsworth.

Green, S., & Salkind, N. (2016). *Using SPSS for Windows and Macintosh: Analyzing and understanding data.* Upper Saddle River, NJ: Prentice Hall.

Greszki, R., Meyer, M., & Schoen, H. (2015). Exploring the effects of removing "too fast" responses and respondents from web surveys. *Public Opinion Quarterly,* 79(2), pp. 471–503.

Griethuijsen, R. A. L. F., Eijck, M. W., Haste, H., Brok, P. J., Skinner, N. C., & Mansour, N., et al. (2014). Global patterns in students' views of science and interest in science. *Research in Science Education,* 45(4), pp. 581–603.

Grindrod, K. A., Li M., & Gates, A. (2014). Evaluating User Perceptions of Mobile Medication Management Applications with Older Adults: A Usability Study. *JMIR Mhealth Uhealth.* 2: e11.

Gunawan, D. D., & Huarng, K. H. (2015). Viral effects of social network and media on consumers' purchase intention. *Journal of Business Research*, 68, pp. 2237–2241.

Gurjar, N. (2018). Understanding Technology Adoption: Theory and Critical Review of Seminal Research. In Langran, E., Borup, J. (Eds.): *Proceedings of Society for*

Information Technology & Teacher Education International Conference 2018. Washington, D.C., United States: Association for the Advancement of Computing in Education (AACE), pp. 846–858.

Gürkut, C., & Nat, M. (2017). Important Factors Affecting Student Information System Quality and Satisfaction, *Eurasia Journal of Mathematics, Science and Technology Education,* 14(3), pp. 923–932.

Gyamf, A., Mensah, Kof, A., & Oduro, G. (2017). Barriers and facilitators to electronic medical records usage in the emergency centre at Komfo Anokye Teaching Hospital, Kumasi-Ghana. *Afr J Emerg Med*.;7: pp.177–182.

Habibov, N., Auchynnikava, A., Luo, R., & Fan, L. (2018), "Who wants to pay more taxes to improve public health care," *International Journal of Health Planning and Management*, 33(4), pp. e944–e959.

Haegele, J. A., & Hodge, S. R. (2015). Quantitative methodology: A guide for emerging physical education and adapted physical education researchers. *Physical Educator*. doi:10.18666/tpe-2015-v72-i5-6133.

Haigh, J. (2018). Information technology in health professional education: why IT matters. *Nurse Educ Today.* 24(7), pp. 547–552. doi: 10.1016/j.nedt.2004.07.008.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th Edition). London, Unites Kingdom: Cengage Learning.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling* (PLS-SEM) (3rd Edition). Thousand Oaks, CA: Sage.

Halawi, L., McCarthy, R., & Aronson, J. (2017). Success stories in knowledge management systems. Issues in Information Systems, 18(1), pp. 64–77.

Hall, J., Fiebig, G. D. & van Gool, K. (2020), "Private finance publicly subsidized: the case of Australian health insurance," in S. Thomson, A. Sagan and E. Mossialos (eds), *Private Health Insurance - History, Politics and Performance*. European Observatory on Health System and Politics. / Aminpour, Sadoughi & Ahamdi, 2014).

Hallquist M., & Wiley, J. (2018). MplusAutomation: An R package for facilitating large-scale latent variable analyses in Mplus. *Structural Equation Modeling*, 25, pp. 621–638.

Hamidi, H., & Jahanshaheefard, M. (2019). Essential factors for the application of education information system using mobile learning: a case study of students of the university of technology. *Telematics Inform.* 38, pp. 207–224.

Hanafizadeh, P., Behboudi, M., Koshksaray, A. A., & Tabar, M. J. S. (2014). Mobile-banking adoption by Iranian bank clients. *Telematics and Informatics*, 31(1), pp. 62–78.

Handayani, P. W., Hidayanto, A. N., Pinem, A. A., Hapsari, I. C., Sandhyaduhita, P. I. & Budi, I. (2017). Acceptance model of a Hospital Information System. *International Journal of Medical Informatics*, 99, pp. 11–28.

Haqani, E. A., & Ahlan, A. R. (2015). Review of knowledge management in higher education. *International Journal of Science and Research (IJSR*), 4(11), pp. 2062–2065.

Harris, M. F., & Zwar, N. A. (2014). Reflections on the history of general practice in Australia. *Med J Aust, 210* (1 Suppl), S37-40. doi: 10.5694/mja14.00141.

Hasanain, R. A., Vallmuur, K., & Clark, M. (2015). Electronic medical record system in Saudi Arabia: Knowledge and preferences of health professionals. *Journal of Health Informatics in Developing Countries,* 9(1), pp. 23-31.

Hussein R, Crutzen R, Gutenberg J, Kulnik ST, Sareban M. & Niebauer J. (2021). Patient-generated health data (PGHD) interoperability: an integrative perspective. In: MIE, 2021 May 27. p. 228–32.

Haughom, J. (2014). "K*nowledge Management in Healthcare: It's More Important Than You Realize.*"

Hawkes, S., K Aulakh, B., Jadeja, N., Jimenez, M., Buse, K., Anwar, I., Barge, S., Odubanjo, M.O., Shukla, A., Ghaffar, A., & Whitworth, J. (2016). *Strengthening capacity to apply health research evidence in policy making experience from four countries. Health Policy and Planning,* 31(2), pp.161-170.

Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. *Evidence-Based Nursing, 18*(3), pp. 66-67.

Health Care. (2017). [Online]. Available at: https://www.merriam-webster.com/dictionary/health%20care. [Accessed 12 September 2021].

Health Systems. (2019). World Health Organisation. [Online]. Available at: *www.who.int*. [Accessed 26 June 2020].

Health Workforce Australia. (2014). Australia's Future Health Workforce – Nurses Overview. [Online]. Available at: https://www.health.gov.au/sites/default/files/documents/2021/03/nurses-australia-s-future-health-workforce-reportsoverview-report.pdf. [Accessed 21 September 2021].

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, pp. 20-25.

Hedt-Gauthier, B. L., Chilengi, R., Jackson, E., Michel, C., Napua, M., Odhiambo, J., & Bawah, A. (2017). Research capacity building integrated into PHIT projects: leveraging research and research funding to build national capacity. *BMC Health Services Research*, 17(3): pp.1-12.

Hemsley, B., Rollo, M., Georgiou, A., Balandin, S., & Hill, S. (2018). The health literacy demands of electronic personal health records (e-PHRs): An integrative review to inform future inclusive research. *Patient Education and Counseling*, 101(1), pp. 2-15.

Hoffmann, T. C., Légaré, F., Simmons, M. B., McNamara, K., McCaffery, K., Trevena, L., & J., Del Mar, C. B. (2016). Shared decision making what do clinicians need to know and why should they bother. *The Medical Journal of Australia*, 201(1), pp. 35-39.

Holmes-Smith, H., Coote, L., & Cunningham, E. (2006). *Structural equation modelling: from the fundamentals to advanced topics.* Melbourne: School Research, Evaluation and Measurement Services.

Holmes-Smith, P. (2011) *Structural Equation Modelling (using AMOS): From fundamentals to advanced topics.* SREAMS; Melbourne, VIC.

Hoogenbosch, B., Postma, J., de Man-van Ginkel, J. M., Tiemessen, N. A., van Delden, J. J., & van Os-Medendorp, H. (2018). Use and the users of a patient portal: Cross-sectional study. *Journal of Medical Internet Research,* 20(9), e262.

Hooper, D., Coughlan, J. & Mullen, M. R. (2008). Structural Equation Modelling: Guidelines for Determining Model Fit. *The Electronic Journal of Business Research Methods,* 6(1), pp. 53 – 60.

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, pp. 76–87.

Hox, J. J., & Bechger, T. M. (1998). An introduction to structural equation modeling. *Family Science Review,* 11, pp. 354-373.

Hsieh, H. L., Kuo, Y. M., Wang, S. R., Chuang, B. K., & Tsai, C. H. (2017). A study of personal health record user's behavioral model based on the PMT and UTAUT integrative perspective. *Int. J. Env. Res. Pub. He.* 14: 8. doi: 10.3390/ijerph14010008.

Huang, F., Teo, T., & Zhou, M. (2020). Chinese students' intentions to use the Internet-based technology for learning. *Educational Technology Research and Development,* 68(1), pp. 575-591.

Immergut, E. M., & Schneider, S., M. (2020). "Is it unfair for the affluent to be able to purchase 'better' healthcare? Existential standards and institutional norms in healthcare attitudes across 28 countries," *Social Science and Medicine*, 267.

Jaafreh, A. B. (2017). 'Evaluation Information System Success: Applied DeLone and McLean Information System Success Model in Context Banking System in KSA', *International review of management and business research*, no. October, pp. 829–845.

Jacob, J. A. (2015). On the road to interoperability, public and private organisations work to connect healthcare data. *Journal of American Medical Association*, 314(12), pp. 1213-1215.

Jain, A. K., & Moreno, A. (2015). *Organizational learning, knowledge management practices and firm's performance: An empirical study of a heavy engineering firm in India. Learning Organization,* 22(1), pp. 14–39.

Jamoom, E. W., Patel, V., Furukawa, M. F., & King, J. (2014). EHR adopters vs. non-adopters impacts of, barriers to, and federal initiatives for EHR adoption. *Healthcare,* 2(1), pp. 33-39.

Janakiraman, R., Lim, J. H., & Rishika, R. (2018). The effect of data breach announcement on customer behavior: Evidence from a multichannel retailer. *Journal of Marketing,* 82(2), pp. 85–105.

Jane, T. (2016). *An Analysis of Nursing Documentation as a Reflection of Actual Nurse Work, Life and Health Library*, 2011, CBS Interactive.

Jang, E. E., Wagner, M., & Park, G. (2016). Mixed methods research in language testing and assessment. *Annual Review of Applied Linguistics*, (34), pp. 123–153.

Jawhari, B., Keenan, L., Zakus, D., Ludwick, D., Isaac, A., Saleh, A., & Hayward, R. (2016). Barriers and facilitators to electronic medical record (EMR) use in an urban slum. *International Journal of Medical Informatics,* 94, pp. 246-254.

Jiang SY. (2017). *A team-based approach to studying complex healthcare processes*. Doctoral dissertation: Columbia University. Thousand Oaks (CA): Sage.

Jöreskog, K. G., & Sörbom, D. (2005). *LISREL 8.72.* Chicago, IL: Scientific Software.

Kahouei, M., Mohammadi, H. B., Majdabadi, H. A., Solhi, M., Parsania, Z., Roghani, P. S., & Firozeh, M. (2014). Nurses' perceptions of usefulness of nursing information system: Module of electronic medical record for patient care in two university hospitals of Iran. *National Center for Biotechnology Information,* 26(1), pp. 30-34 [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3990381/. [6 July 2018].

Kamble, S. S., Gunasekaran, A., Subramanian, N., Ghadge, A., Belhadi, A., & Venkatesh, M. (2021). Blockchain technology's impact on supply chain integration and sustainable supply chain performance: Evidence from the automotive industry. *Annals of Operations Research,* pp. 1-26.

Kankam, P. K. (2019). The use of paradigms in information research. *Library & Information Science Research,* 41(2), pp. 85-92. doi: 10.1016/j.lisr.2019.04.003.

Kanyua, N. H. (2015). ‘*Factors influencing the adoption of ICT in Public hospitals in Nairobi’, Master’s Thesis, Department of Extra-Mural Studies, University of Nairobi.*

Karakaya-Ozyer, K., & A. D. (2018). A Review of Structural Equation Modelling Applications in Turkish Educational Science Literature, 2010-2015. *International Journal of Research in Education and Science (IJRES)*.

Karekezi, S., Kimani, J., Onguru, O., & Kithyoma, W. (2012). Energy Security and Adaptation to Climate Change in East Africa and the Horn of Africa: large scale Hydropower versus decentralized renewables AFREPREN/FWD *Occasional Papers Series.*

Karmann, A., & Roesel, F. (2017). Hospital Policy and Productivity – Evidence from German States. *Health Economics*, 26, pp. 1548–1565.

Karsh, B., T. Weinger, M., B. & Abbott, P., A. (2018). Health information technology: fallacies and sober realities. *J Am Med Inform Assoc*:17: pp. 617–623.

Katehakis, D. G., & Kouroubali, A. A. (2019). Framework for e-Health Interoperability Management. J Strateg Innov Sustain. 14(5), pp. 51–61.

Katurura M., & Cilliers L. (2017). A review of the implementation of electronic health record systems on the African continent. *Proceedings of African Computer and Information System & Technology Conference;* 10–11 July 2017, Cape Town, South Africa.

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 and Family Medicine,* 10(1), pp. 1-8. DOI:10.4102/phcfm. v10i1.1746.

Katuu, S., & Management, T. P. (2016). Transforming South Africa’s health sector: The eHealth Strategy, the implementation of electronic document and records management systems (EDRMS) and the utility of maturity models. *J. Sci. Technol. Policy Manag.* 2016(7), pp. 330–345.

Kern, L. M., Edwards, A., & Kaushal, R. (2016). The patient-centered medical home, electronic health records, and quality of care. *Ann Intern Med,* 160(11), pp. 741-749. doi: 10.7326/m13- 1798.

Keyworth, C., Hart, J., Armitage, C. J., & Tully, M. P. (2018). What maximizes the effectiveness and implementation of technology-based interventions to support healthcare professional practice? A systematic literature reviews. *BMC medical informatics and decision making*,18, p. 93.

Kgasi, M. R., & Kalema, B. M. (2014). Assessment eHealth readiness for rural South African areas. *J Ind Intell Inform.* 2(2), pp. 131-135.

Khaldi, K. (2017). Quantitative, qualitative, or mixed research: which research paradigm to use? Journal of Educational and Social Research, 7(2), p.15. doi:10.36941/jesr.

Khalifa, M. (2014). Technical and Human Challenges of Implementing Hospital Information Systems in Saudi Arabia. *Journal of Health Informatics in Developing Countries*, 8(1).

Khwima, E., Msiska, M., Kumitawa, A., & Kumwenda, B. (2017). Factors affecting the utilisation of electronic medical records system in Malawian central hospitals. *Malawi Medical Journal 29* (3), pp. 247–253.

Kiberu, V. M., Mars, M., & Scot, R. E. (2017). Barriers and opportunities to implementation of sustainable e-Health programmes in Uganda: A literature review. *African Journal of Primary Health Care and Family Medicine,* 9(1), pp. 1- 10.

Kiberu, V. M., Matovu, J. K., Makumbi, F., Kyozira, C., Mukooyo, E., & Wanyenze, R. K. (2014). Strengthening district-based health reporting through the district health management information software system: the Ugandan experience. *BMC Med Inform Decis Mak*. 14: pp. 1–9.

Kim, H., Ku, B., Kim, J. Y., Park, Y. J., & Park, Y. B. (2016). Confirmatory and exploratory factor analysis for validating the phlegm pattern questionnaire for healthy subjects. *Evid. Based Complement. Alterna*t. Med. 2016, pp. 1–8. doi: 10.1155/2016/2696019.

Kimathi, F. A., & Zhang, Y. (2019). Exploring the general extended technology acceptance model for e-learning approach on student's usage intention on e-learning system in University of Dar es Salaam. *Creative Education,* 10(01), p. 208.

Kimberlin, C. L., & Winterstein, A. G. (2008). "Validity and Reliability of Measurement Instruments Used in Research," *American Journal of Health-System Pharmacists,* 65(1), pp. 2276-2284.

Kivunja, C., & Kuyini, A. B. (2017). Understanding and Applying Research Paradigms in Educational Contexts. *International Journal of Higher Education.*6 (5). [Online]. Available at: https://doi.org/10.5430/ijhe.v6n5p26. [Accessed 16 September 2021].

Kline, R. B. (2016). *Principles and Practice of Structural Equation Modeling* (4th ed.). New York, NY: Guilford Publications.

Kocher, R. P. (2021). Reducing Administrative Waste in the US Health Care System. *JAMA,* 325(5), pp.427–428.

Koech, M. C., Duncan, A., & Damaris O. (2017). *Assessment of Medical Records Management in Support of Service Delivery at Moi Teaching and Referral Hospital, Eldoret Kenya. An International Publisher for Academic and Scientific Resources.*

Kohli, R., & Tan, S. S. L. (2016). Electronic health records: How can IS researcher contribute to transforming healthcare? *MIS Quarterly*, 40(3), pp. 553–573. doi:10.25300/MISQ/2016/40.3.02.

Kooij, L., Groen, W. G., & Van Harten, W. H. (2018). Barriers and Facilitators Affecting Patient Portal Implementation from an Organisational Perspective: Qualitative Study. *Journal of Medical Internet Research,* 20(5), p. e183. DOI: 10.2196/jmir.8989.

Koul, S., & Eydgahi, A. (2017). A systematic review of technology adoption frameworks and their applications. *Journal of technology management & innovation*, 12(4), pp. 106–113. DOI: 10.4067/S0718-27242017000400011.

Kouroubali, A., & Katehakis, D. G. (2019). The new European interoperability framework as a facilitator of digital transformation for citizen empowerment. *Journal of Biomedical Informatics,* 94, 103166.

KPMG Africa. (2012). *The state of healthcare in Africa*. KPMG.

Krist, A. H., Beasley, J. W., Crosson, J. C., Kibbe, D. C., Klinkman, M. S., Lehmann, C. U., & Waldren, S. E. (2014). Electronic health record functionality needed to better support primary care. *Journal of the American Medical Informatics Association,* 21, pp. 764–771. doi:10.1136/amiajnl-2013-002229.

Kristensen, N., Nymann, C., & Konradsen, H. (2015). Implementing research results in clinical practice-the experiences of healthcare professionals. *BMC Health Serv Res.* 2015; 16(1), pp. 1–10.

Krousel-Wood, M, McCoy, A. B., & Ahia, C, (2018). Implementing electronic health records (EHRs): Health care provider perceptions before and after transition from a local basic EHR to a commercial comprehensive EHR. *J Am Med Informatics Assoc.* 25(6), pp. 618-626. doi:10.1093/jamia/ocx094.

Kruse, C. S., Kristof, C., Jones, B., Mitchell, E., & Martinez, A. (2016). Barriers to electronic health record adoption: a systematic literature review ‘, *Journal of Medical Systems*, 40(12), p. 252.

Kruk, M. E., Gage, A. D., Arsenault, C., Jordan, K., Leslie, H. H., Roder-DeWan, S., Adeyi, O., Barker, P., Daelmans, B., Doubova, S. V., English, M., García-Elorrio, E., Guanais, F., Gureje, O., Hirschhorn, L. R., Jiang, L., Kelley, E., Lemango, E. T., Liljestrand, J., Malata, A., Marchant, T., Matsoso, M. P., Meara, J. G., Mohanan, M., Ndiaye, Y., Norheim, O. F., Reddy, K. S., Rowe, A. K., Salomon, J. A., Thapa, G., Twum-Danso, N. A. Y., & Pate, M. (2018). High-Quality Health Systems in the Sustainable Development Goals era: Time for a Revolution. Lancet Global Health Comm. 2018; 6(11), pp. 196–252.

Kumar, M., & Mostafa, J. (2019). Research evidence on strategies enabling integration of electronic health records in the health care systems of low- and middle-income countries: A literature review. *The International Journal of Health Planning and Management,* 34(2), pp. e1016–e1025.

Kumar, M., Mostafa, J., & Ramaswamy, R. (2017). Federated health information architecture: Enabling healthcare providers and policymakers to use data for decision-making. *Health Information Management Journal,* 1833358317709704.

Kunaifi, A. (2021). Quantitative Easing in Overcoming the Crisis: Criticism ofQeinthe Monetary System Of Capitalism. *Turkish Journal of Computer and Mathematics Education* (TURCOMAT), 12(3), pp. 3703-3714.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, 14(1), pp. 21-38.

Lau, F., & Kuziemsky, C. (2016). *Handbook of eHealth Evaluation: An Evidence-Based Approach.* University of Victoria.

Laukka, E., Huhtakangas, M., Heponiemi, T., & Kanste, O. (2020). Identifying the roles of healthcare leaders in HIT implementation: A scoping review of the quantitative and qualitative evidence. *International Journal of Environmental Research and Public Health*, 17(8), p. 2865.

Lee, H. S., (2017). 'Knowledge management enablers and process in hospital organizations', *Osong Public Health and Research Perspectives*, 8(1), pp. 26-33.

Lee, J. L., Dy, S. M., Gurses, A. P., Kim, J. M., Suarez-Cuervo, C., Berger, Z. D., Brown, R., & Xiao, Y. (2018). Towards a more patient-centered approach to medication safety. *J. Patient Exp.*5(2), pp. 83–87.

Leedy, P. L., & Ormrod, J. E. (2015). *Practical research: Planning and design* (11th Edition). London: Pearson Education.

Légaré, F., & Witteman, H. O. (2016). Shared decision-making examining key elements and barriers to adoption into routine clinical practice. *Health Aff* 13(32), pp. 276–284. 10.1377/hlthaff.2012.1078.

Lew, S. L., Lau, S. H., & Leow, M. C. (2019). Usability factors predicting continuance of intention to use cloud e-learning application. Heliyon, 5(6), p. e01788. [Online]. Available at: https://doi.org/10.1016/j.heliyon.2019.e01788. [Accessed 16 November 2020].

Li, R., Pei, S., Chen, B., Song, Y., Zhang, T., Yang, W., & Shaman, J. (2020). Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2) *Science (New York, NY).* 368(6490), pp. 489–493.

Liu, X. (2010). Empirical testing of a theoretical extension of the technology acceptance model: An exploratory study of educational wikis. *Communication Education*, 59(1), pp. 52-69.

LoBiondo-Wood, G., Faan, P. R., Haber, J., & Faan, P. R. (2021). *Nursing Research E-Book: Methods and Critical Appraisal for Evidence-Based Practice*. Elsevier Health Sciences; 2021.

Lovell, T. (2019). Germany introduces Digital Supply Act to digitalise healthcare. [Online]. Available at: https://www.healthcareitnews.com/news/europe/germany-introduces-digital-supply-act-digitalise-healthcare. [Accessed 16 September 2021].

Lowry, P. B., & Gaskin, J. (2014). Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE Transactions on Professional Communication, 57*(1-2), pp. 123–146.

Lulin, Z., Yiranbon, E., & Asante Antwi, H. (2016). Complementarity of clinician judgment and evidence-based models in medical decision-making antecedents, prospects, and challenges*. BioMed Research International*, pp. 1-11.

Luna, D., Almerares, A., Mayan, J. C., Gonzalez-Bernaldo-de-Quiros, F., & Otero, C. (2014). Health informatics in developing countries: going beyond pilot practices to sustainable implementations: a review of the current challenges. *Healthc Inform Res.* 20(1), pp. 3–10. doi: 10.4258/hir.

Luthuli, L. P. (2017). *Medical records management practices in public and private hospitals in Umhlathuze area, South Africa. Master's dissertation*. University of Zululand.

MacKinnon D. P. (2017). Integrating mediators and moderators in research design. *Research on Social Work Practice*, 21(6), pp. 675–681.

Maduku, D. K., Mpinganjira, M., & Duh, H. (2016). 'Understanding mobile marketing adoption intention by South African SMEs: A multi-perspective framework', *International Journal of Information Management*, 36(5), pp. 711-723.

Mahmood, N., Burney, A., Abbas, Z., & Rizwan, K. (2012). Data and Knowledge Management in Designing Healthcare Information Systems. *International Journal of Computer Applications,* 50(2), pp. 34-39.

Manaktala, S., & Claypool, S. R. (2017). Evaluating the impact of a computerized surveillance algorithm and decision support system on sepsis mortality. *J. Am. Med. Inform. Assoc.* 24, pp. 88–95.

Mantas, J., Househ, M. S., & Hasman, A. (2014). *Integrating information technology and management for quality of care, IOS Press,* Amsterdam, US.

Manyisaa, Z. & van Aswegenb, E. (2017). Factors affecting working conditions in public hospitals: A literature review. *International Journal of Africa Nursing Sciences*, 6, pp. 28-38.

Maranguni, N., & Grani, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal Access in the Information Society*, *14*(1), pp. 81-95.

Marcoulides, K. M., & Yuan, K. H. (2017). New ways to evaluate goodness of fit: A note on using equivalence testing to assess structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, 24(1), pp. 148-153.

Marutha, N., & Ngoepe, M. (2017). The role of medical records in the provision of public healthcare services in the Limpopo province of South Africa. South African *Journal of Information Management,* 19(1), pp. 1-8.

Marutha, N. S. & Ngoepe, M. (2018). Medical records management framework to support public healthcare services in Limpopo province of South Africa. *Records Management Journal,* 28(2), pp. 187–203.

Marutha, N. S. (2016). *A framework to embed medical records management into the healthcare service delivery in Limpopo Province of South Africa.* Pretoria: University of South Africa.

Matikiti, R., Mpinganjira, M., & Roberts-Lombard, M. (2018). Application of the Technology Acceptance Model and the Technology–Organisation–Environment Model to examine social media marketing use in the South African tourism industry. *South African Journal of Information Management.* 20(1).

Mchunu, N. N. (2012). *Adequacy of healthcare information systems to support data quality in the public healthcare sector, in the Western Cape, South Africa* (Doctoral dissertation, Cape Peninsula University of technology).

McMullen, P. C., Howie, W. O., Philipsen, N., Bryant, V. C., Setlow, P. D., Calhoun, M. et al., (2014). ‘Electronic medical records and electronic health records: Overview for nurse practitioners’, *The Journal for Nurse Practitioners*, 10(9), pp. 660-665.

McNeish, D., An, J., & Hancock, G. R. (2018). The thorny relation between measurement quality and fit index cut-offs in latent variable models. *Journal of Personality Assessment*, 100(1), pp. 43-52. 10.1080/00223891.2017.1281286.

Meditech, (2018). *Meditech expands solutions in the KwaZulu-Natal Province of South Africa.* [Online]. Available at: https://ehr.meditech.com/news/meditech-expands-solutions-in-the-kwazulu-natal-province-of-south-africa-0 [Accessed 16 September 2021].

Medsker, G. J., Williams, L. J., & Holahan, P. J. (1994). A review of current practices for evaluating causal models in organisational behavior and human resources management research. *Journal of Management,* 20, pp. 439–464.

Meeks, D. W., Takian, A., Sittig, D. F. (2018). Exploring the sociotechnical intersection of patient safety and electronic health record implementation. *J Am Med Inform Assoc*:21(e1), p. e2834.

Menon, S., Singh, H., Meyer, A. N., Belmont, E., & Sittig, D. F. (2016). Electronic health record related safety concerns: A cross-sectional survey. *Journal of Healthcare Risk Management,* 34(1), pp. 14-26.

Mertler, C. A., & Reinhart, R. V. (2017). *Advanced and multivariate statistical methods: Practical application and interpretation* (6^{th} Edition). Routledge.

Middleton, B., Bloomrosen, M., & Dente, M., A. (2017). Enhancing patient safety and quality of care by improving the usability of electronic health record systems: recommendations from AMIA. *J Am Med Inform Asso*c.13(20), pp. e2–8.

Mikk, K. A., Sleeper, H. A., & Topol, E. J. (2017). The pathway to patient data ownership and better health. *Journal of the American Medical Association.* 318(15), pp. 1422-1434. doi:10.1001/jama.12145.

Mills, J. (2014). *JAC – Supplier Profile. Nootroclin - A Fluid Health Information System.*

Mind Matter. (2018). *Nootroclin.* [Online]. Available at: http://mindmatter.co.za/index.php/blog/item/72-nootroclin-fluid-health-information-system. [Accessed 07 September 2021].

Ministry of Health (MOH) A. (2019). *Press Release: Government launches the Health Sector Integrated Refugee Response Plan* (2019–2024). [Online]. Available at: https://health.go.ug/download/file/fid/2102. [Accessed 16 September 2021].

Ministry of Health and Social Affairs (2022). God och nära vård 2022 - En omställning av hälso- och sjukvården med primärvården som nav. Överrenskommelse mellan staten och Sveriges Kommuner och Regioner. Available at: https://www.regeringen.se/overenskommelser-och-avtal/2022/01/god-och-nara-vard---overenskommelse-mellan-staten-och-sveriges-kommuner-och-regioner/. [Accessed 13 June 2020].

Ministry of Health B. (2014). *Holistic Assessment of Health Sector Programme of Work 2014,* Ministry of Health, Accra Ghana. [Online]. Available at: http://www.moh-ghana.org/UploadFiles/Publications/Holistic%20Assessment%20Report%20June%202014140811072318.pdf [Accessed 16 September 2021].

Mishra, P., Singh, U., Pandey, C., Mishra, P., & Pandey, G. (2019). Application of student's t-Test, analysis of variance, and covariance. *Annals of Cardiac Anaesthesia*, 22(4), p. 407. Web.

Misto, K., Padula, C., Dame, L., Molloy, P., & Nimmagadda, J. (2020). Interprofessional evidence-based strategies to enhance provider and patient interactions during electronic health record use. *J Nurses Prof Dev.* 36(3), pp. 134–140.

Mitchell, G., J. (2016). Implications of holding ideas of evidence-based practice in nursing. *Nurs Sci Q.* 2016; 26(2), pp. 143–151.

Mndzebele, S., & Tshivhase, S. (2016). Application of evidence-based nursing practice at a tertiary hospital in Pretoria, Gauteng province, South Africa. PULA: *Botswana Journal of African Studies,* 30(1): pp.166-173.

Mohamadali Noor, A., & Zahari, N. A. (2017). The organisation factors as barrier for sustainable health information systems (HIS): a review. *4th information systems international conference 2017,* ISICO 2017, 6–8 November 2017, Bali, Indonesia. Procedia Comput Sci.;124, pp.354–361.

Moshagen, M. (2012). The model size effect in SEM: Inflated goodness-of-fit statistics are due to the size of the covariance matrix. *Structural Equation Modeling: A Multidisciplinary Journal, 19, pp. 86-98.*

Moslehpour, M., Pham, V., Wong, W. K., & Bilgiçli, İ. (2018). *e-Purchase intention of Taiwanese consumers: Sustainable mediation of perceived usefulness and perceived ease of use.* Sustainability, 10(1), p. 234.

Mostert-Phipps, N. (2018). '*Health information technologies for improved continuity of care: a South African perspective', PhD Thesis, Faculty of Engineering, the Built Environment and Information Technology, Nelson Mandela Metropolitan University*, Port Elizabeth.

Moudatsou, M.; Stavropoulou, A.; Philalithis, A., & Koukouli, S. (2020). *The role of empathy in health and social care professionals.* Healthcare, 8, p. 26.

Moullin, J. C., Ehrhart, M. G., & Aarons, G. A. (2018). The role of leadership in organisational implementation and sustainment in service agencies. *Research on Social Work Practice*, 28(5): pp.558–567.

Msiska, K.E.M. Kumitawa, A., & Kumwenda, B. (2017). Factors affecting the utilisation of electronic medical records system in Malawian central hospitals: *Malawi Medical Journal;* 29(3), pp. 247 – 23.

Msomi, M. (2020). *Change management in the implementation of electronic health records systems in public and private hospitals in the eThekwini area, South Africa. Masters thesis.* University of Zululand.

Mtebe, J. S., Nakaka, R., International, A., & Alliance, H. (2018). Journal of Health Informatics in Developing Countries Submitted: July 10 th, 2018 Accepted: September 8 th, 2018 *Assessing Electronic Medical Record System Implementation at Kilimanjaro Christian,* 12(2), pp. 1–16.

Mugo, D. M., & Nzuki, D. (2014). Determinants of Electronic Health in Developing Countries. *International Journal of Arts and Commerce.*, 3(30), pp. 49-60.

Muhanga, M. I. (2020). Health Literacy and Health Behaviour under One Health Approach in Tanzania: Connecting the Connected or Connecting the Unconnected? *East African Journal of Social and Applied Sciences, 2* (2), pp. 124-137.

Muhanga, M.I., & Malungo, J.R. (2018). *Health Literacy and Some Socio-Demographic Aspects under One Health Approach in Eastern Tanzania: Connections and Realities. Urban Studies and Public Administration,* 1(1), pp. 89- 100.

Mukasa, N. (2012). Uganda Healthcare system profile: Background, organisation, polices and challenges. *Journal of Sustainable regional health system,* (1), pp.1-36.

Mukhles, M. A. A. (2020). Linking Ontology, Epistemology and Research Methodology. *Science & Philosophy,* 8(1), pp. 75-91.

Murti, A., Deshpande, A., & Srivastava, N. (2013). Service quality, customer (Patient) satisfaction and behavioural intention in health care services: exploring the Indian perspective. *J Health Manage.* 15(1), pp. 29–44.

Mustillo, S., & Kwon, S. (2015). Auxiliary variables in multiple imputation when data are missing not at random. *The Journal of Mathematical Sociology,* 39 (2), pp. 73–91.

Mutsagondo, S. & Chaterera, F. (2016). *Mirroring the National Archives of Zimbabwe Act in the context of electronic records: lessons for ESARBICA member states. Information Development* 32(3), 254-259.

Mutsagondo, S. & Tsvuura, G. (2017). Dilemma in disposing electronic mail records in public departments: the Zimbabwean Scenario. *Paradigms: A Research Journal of Commerce, Economics and Social Sciences* 11(2), pp. 190-195.

Nabukeera, M. (2016). Challenges and barriers to the health service delivery system in Uganda. IOSR *Journal of Nursing and Health Science (IOSR-JNHS)* e-ISSN: 2320–1959.p- ISSN: pp. 2320–1940, 5(2) Ver. V (Mar. - Apr. 2016), pp. 30-38.

Naeem, S. B., Bhatti, R., & Ishfaq, K. (2017). Nurses' attitude and belief toward evidence-based nursing practices in Tertiary Care Hospitals of Multan, Pakistan. *ISRA Medical Journal,* 9: pp. 101-105.

Nahurira, E., Businge, J., & Nakato, R. (2016). A framework for assessing information systems adoption and utilisation in the healthcare. *Int. J. Comput. Trends Technol.* 39(2), pp. 89–99.

Nakisozi, L. (2014). *National health care system in Uganda.* [Online]. Available at: https://ghcorps.org/national-health-care-system-in-uganda/. [Accessed 16 September 2021].

Nassiwa, J. (2019). *Factors Affecting Adoption of Mobile Banking in Uganda: A Case Study of Stanbic Bank, Makerere University Branch.* Doctoral Dissertation, Kampala: Makerere University.

National Academies of Sciences, Engineering, and Medicine. (2015). *Improving diagnosis in health care.* Washington (DC): National Academies Press.

Naumann, L., Esdar, M., Ammenwerth, E., Baumberger, D. & Hübner Ursula. (2019). Same goals, yet different outcomes: analysing the current state of ehealth adoption and policies in Austria, Germany, and Switzerland using a mixed methods approach. *Stud Health Technol Inform.* 2019 Aug 21; 264: pp. 1012–1016.

Neuman, W. L. (2014). *Social research methods: Qualitative and quantitative approaches*. Essex: Pearson Education Limited.

Nevhutalu, H. K. (2016). '*Patients' rights in South Africa's public health system: Moral-critical perspectives'*, PhD Degree in Philosophy, University of Stellenbosch.

Ngidi, T. (2015). *Management of medical records: a study at Princess Marina Hospital-Gaborone, Botswana. Master's Thesis, University of Botswana, Gaborone.* Available at: https://ubrisa.ub.bw/bitstream/handle/ 10311/1461/Ngidi_%20Unpublished%20%28MA%29_2015.pdf? sequence¼3&isAllowed¼y [Accessed 12 April 2019].

Nguyen, L., Bellucci, E. & Nguyen, L. T. (2014). Electronic health records implementation: An evaluation of information system impact and contingency factors. *International Journal of Medical Informatics* 83(11), pp. 779-796).

Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. *Computers & Education,* 109: pp. 56-73.

Nissinboim, N., & Naveh, E. (2018). Process standardization and error reduction: *A revisit from a choice approach. Safety science,* 103, pp. 43-50.

Noh J. W., Im Y. M., Kim K. B., Kim M. H., Kwon Y. D. & Cha J. (2021). Digital and economic determinants of healthcare in the crisis-affected population in Afghanistan: access to mobile phone and socioeconomic barriers. Healthcare . 9(5):p. 506. doi: 10.3390/healthcare9050506.

Nysveen, H., Pedersen, P. E. & Skard, S. E. R. (2015). A review of mobile services research: Research gaps and suggestions for future research on mobile apps, SNF Working Paper No. 01/15, *Centre for Applied Research at NHH,* Bergen.

O'Connor, S., Hanlon, P., Garcia, S., Glanville, J., O'Donnell, C. A., & Mair, F. S. (2016). Barriers and facilitators to engagement and recruitment to digital health interventions: protocol of a systematic review of qualitative studies. *BMJ Open* 6e010895.

O'Donnell, A., Kaner, E., Shaw, C., & Haighton, C. (2018). Primary care physicians' attitudes to the adoption of electronic medical records: a systematic review and evidence synthesis using the clinical adoption framework. *BMC Medical Informatics and Decision Making,18* (1), 101. [Online]. Available at: http://doi.org/10.1186/s12911-018-0703-x. [Accessed 14 September 2020].

Oberg, U., Orre, C. J., Isaksson, U., Schimmer, R., Larsson, H., & Hornsten,¨ A. (2018). Swedish primary ˚ healthcare nurses' perceptions of using digital ehealth services in support of patient self-management. *Scandinavian journal of caring sciences,* 32(2), pp. 961–970.

Odekunle, F. F., Odekunle, R. O., & Shankar, S. (2017). Why sub-Saharan Africa lags in electronic health record adoption and possible strategies to increase its adoption in this region. *International Journal of Health Sciences,* 11(4), pp. 59–63. PMid:29085270; PMCid: PMC5654179.

Ohuabunwa, E. C., Sun, J., Jubanyik, K. J. & Wallis, L. A., (2015), 'Electronic medical records in low to middle income countries: The case of Khayelitsha Hospital, South Africa', *African Journal of Emergency Medicine*, 6(1), pp. 38–43.

Ojo, A. I., & Popoola, S. O. (2015). Some Correlates of Electronic Health Information Management System Success in Nigerian Teaching Hospitals: *Biomedical Informatics Insights;* 7: pp. 1-9.

Ojo, A. I. (2017). Validation of the DeLone and McLean Information Systems Success Model. *Healthcare Informatics Research*, 23 (1), pp. 60-66.

Olayiwola, J. N., Anderson, D., Jepeal, N., Aseltine, R., Pickett, C., & Yan, J. (2016). Electronic consultations to improve the primary care-specialty care interface for cardiology in the medically underserved: a cluster-randomized controlled trial. *Ann Fam Med*; 14, pp. 133-14.

Oliveira, T., & Martins, M. F. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *The Electronic Journal Information Systems Evaluation*, 14(1), pp. 110–121.

Oluoch, T., Muturi, D., Kiriinya, R., Waruru, A., Lanyo, K., Nguni, R., Ojwang, J., Waters, K. P., & Richards, J. (2018). 'Do interoperable national information systems enhance 97 availabilities of data to assess the effect of scale-up of HIV services on health workforce deployment in resource-limited countries?', in *Studies in Health Technology and Informatics*, pp. 677–681.

Oluseye, O. M., Kehinde, D. R., Akingbade, O., & Ogunlade, O. L. (2019). knowledge and utilisation of referral system among health care workers in selected primary health care centers in oyo state Nigeria. *Journal of community medicine and primary health care.* 31(1), pp. 67-72.

Omar, A. S., Razak, M. R. A., Yasin, M. H. M., & Dauwed, M. (2018). Validity and reliability questionnaire for social, environment and self-efficacy related of deaf adolescents' physical activity. *Journal of Theoretical and Applied Information Technology,* 96(21), pp. 7041-7054.

Opeke, R. O., & Opele, J. K. (2014). Assessment of knowledge sharing behaviours of postgraduate students in selected Nigerian universities. *Information and Knowledge Management,* 4(11), pp. 102–107.

Opele, J. K., Adepoju, K. O., & Adegbite, W. M. (2020). Barriers to knowledge management practices, interprofessional collaboration and information technology application in Federal Tertiary Hospitals in Nigeria. *Canadian Social Science*, 16(12), pp. 35–41.

Osborne, Jason W. & Waters, Elaine (2019). "Four assumptions of multiple regression that researchers should always test," *Practical Assessment, Research, and Evaluation: 8(2).*

Ostlund, B. (2017). Digitizing health care: Welfare technology as a way to meet digital and demographic challenges in Sweden. *In 2017 4th International Conference on Systems and Informatics (ICSAI),* pp. 78– 83. IEEE.

Owolabi, A. K., Mhlongo, T. P., & Evans, N. (2016). The status and challenges of clinical informatics development of South Africa. Inkanyiso: *Journal of Humanities & Social Sciences,* 8(2), pp. 125-135.

Oyeyemi, S.O., & Wynn, R. (2014). Giving cell phones to pregnant women and improving services may increase primary health facility utilisation: a case-control study of a Nigerian project. *Reproductive Health*, 11(1), p.8.

Pai, F. Y., & Huang, K. I. (2016). Applying the Technology Acceptance Model to the Introduction of Healthcare Information Systems, *Technological Forecasting and Social Change,* 78(4), pp. 650-660.

Pal, M., & Bharati, P. (2019). Introduction to correlation and linear regression analysis. *In Applications of Regression Techniques.* pp. 1-18. Springer, Singapore.

Palabindala, V., Pamarthy, A., & Jonnalagadda, N. R. (2016). Adoption of electronic health records and barriers. *Journal of Community Hospital Internal Medicine Perspectives*, *6*(5), pp. 1-3.

Pallant, J., & Routledge. (2020). *SPSS Survival Manual: A Step-by-Step Guide to Data Analysis Using IBM SPSS.*

Pan, Y., Froese, F., Liu, N., Hu, Y., & Ye, M. (2022). The adoption of artificial intelligence in employee recruitment: The influence of contextual factors. *The International South Asian Journal of Human Resources Management Journal of Human Resource Management,* 33(6), pp. 1125–1147.

Panagiotopoulos, P., & Barnett, J. (2015). Social media in union communications: An international study with UNI global union affiliates. *Br J Ind Relat,* 53(3), pp. 508–532. doi: 10.1111/bjir.12060.

Patel, V. L., & Kannampallil, T. G. (2014). Human factors and health information technology: current challenges and future directions. *Yearbook of medical informatics.*14; 9(1), p. 58.

Patkar, M., Price, D., & Lee, J. (2016). *The Effects Power Outages Can Have On Your Computer.* [Online]. Available at: http://www.makeuseof.com/tag/effects-power-outages-can-computer/. [Accessed 16 September 2021].

Pawar P., Parolia N., Shinde S., Edoh T. O. & Singh M. (2021) eHealth Chain—a blockchain-based personal health information management system. Annals of Telecommunications. 77(1-2):33–45. doi: 10.1007/s12243-021-00868-6.

Pelaccia, T., Messman, A. M., & Kline, J. A. (2020). '*Misdiagnosis and failure to diagnose in emergency care: Causes and empathy as a solution', Patient Education and Counseling.* 103, pp. 1650–1656.

Pham, C. D., Vu, S. T., Pham, Y. T. K., & Vu, N. T. (2020). Evaluating Performance of Vietnamese Public Hospitals Based on Balanced Scorecard. *Journal of Asian Finance, Economics and Business,* 7(6), pp. 339–349.

Phan, D. T. T., Nguyen, T. T. H., & Bui, T. A. (2019). Going beyond Border? Intention to Use International Bank Cards in Vietnam. *Journal of Asian Finance, Economics and Business,* 6(3), pp. 315-325.

Pitt, L. F., Watson, R. T., & Kavan, C. B. (1995). Service quality: a measure of information systems effectiveness. *MIS quarterly,* pp. 173-187.

Plantier, M., Havet, N., Durand, T., Caquot, N., Amaz, C., Philip, I., Biron, P., & Perrier, L. (2017). Does adoption of electronic health records improve organisational performances of hospital surgical units? Results from the French e-SI (PREPS-SIPS) study. *Int. J. Med. Inform.*2017; 98, pp. 47–55.

Pletcher, T., Livesay, J., & Mach, R. (2018). U.S. *Patent Application* No. 10/120,978. [Online]. Available at: https://patents.justia.com/inventor/timothy-pletcher. [Accessed 16 September 2021].

Polit, D. F., & Beck, C. T. (2017). *Nursing Research: Generating and Assessing Evidence for Nursing Practice (10th Ed.).* Wolters Kluwer Health, Philadelphia.

Pomykalski, J. J., Dion, P., & Brock, J. L. (2008). A structural equation model for predicting business student performance. *Journal of Education for Business*, 83(3), pp. 159-164.

Postema, T. R, Peeters, J. M., & Friele, R. D. (2012) Key factors influencing the implementation success of home telecare application; *International Journal of Medical Information;* 81(6), pp. 415–23.

Prosci. (2020). Five levers of organisational change management, [Online]. Available at: https://www.prosci.com/resources/articles/five-levers-oforganisational-change-management. [Accessed 16 September 2021].

Purohit, A., Smith J., & Hibble, A. (2021). Does telemedicine reduce the carbon footprint of healthcare? A systematic review. *Future Healthcare Journal.* 8(1), p. e85.

Pyrene, M. B. (2015). *The management of records for healthcare service delivery at the Victoria Public hospital in the Eastern Cape Province in South Africa.* Master's thesis. University of Fort Hare.

Queirós, A., Faria, D., & Almeida, F. (2017). Strengths and Limitations of Qualitative and Quantitative Research Methods. *European Journal of Education Studies,* 3, pp. 369-387.

Rahman, M. M., Strawderman, L., Lesch, M. F., Horrey, W. J., Babski-Reeves, K., & Garrison, T. (2018). Modelling Driver Acceptance of Driver Support Systems. *Accid. Anal. Prev. 121*, pp. 134–147.

Rechberg, I. (2018). Knowledge management paradigms, philosophicalassumptions: An outlook on future research. *American Journal of Management*, 18(3), pp. 61–74.

Rehfuess, E. A., Durão, S., Kyamanywa, P., Meerpohl, J. J., Young, T., & Rohwer, A. (2016). *An approach for setting evidence-based and stakeholder-informed research priorities in low-and middle-income countries.* Bulletin of the World Health Organisation, 94(4), p. 297.

Reid, D. A. (2018). Abductive reasoning in mathematics education: Approaches to and theorisations of a complex idea. *Eurasia Journal of Mathematics, Science and Technology Education,* 14(9).

Reis, W. C., Bonetti, A. F., Bottacin, W. E., Reis, A. S. Jr., Souza, T., T., Pontarolo, R, Correr, C. J., & Fernandez-Llimos, F. (2017). *Impact on process results of clinical decision support systems (CDSSs) applied to medication use: overview of systematic reviews. Pharm Pract (Granada).* https://doi.org/10.18549/PharmPract.2017.04.1036. [Accessed 16 September 2021].

Renolen, Å., Høye, S., Hjälmhult, E., Danbolt, L. J., & Kirkevold, M. (2018). "Keeping on track"—Hospital nurses' struggles with maintaining workflow while seeking to integrate evidence-based practice into their daily work: A grounded theory study. International *Journal of Nursing Studies,* 77, pp. 179-188.

Rho, M. J., Yoon, K. H., Kim, H. S., & Choi, I. Y. (2015). Users' perception on telemedicine service: A comparative study of public healthcare and private healthcare. *Multimedia Tools and Applications*, 74(7), pp. 2483–2497. doi:10.1007/s11042-014-1966-6.

Riksdagen. (2018). Primärvårdens uppdrag borde definieras Riksdagen. [Online]. Available at: http://www.riksdagen.se/sv/aktuellt/2018/apr/24/primarvardens-uppdrag-borde-definieras/ [Accessed 16 September 2021].

Riso, B., Tupasela, A., Vears, D. F., Felzmann, H., Cockbain, J., Loi, M., Kongsholm, N. C., Zullo, S., & Rakic, V. (2017). Ethical sharing of health data in online platforms–which values should be considered? *Life sciences, society, and policy,* 13(1), pp. 12-19.

Robertson, J. (2013). *Top 10 Countries Where Doctors Go Digital*, [Online]. Available at: http://www.bloomberg.com/slideshow/2013-06-25/top-10-countries-where-doctors-go-digital.html#slide1. [Accessed 16 September 2021].

Rohani, J. M., Yusof, S. M., & Mohamad, I. (2009). The relationship between statistical process control critical success factors and performance: A structural equation modeling approach. *International Conference on Industrial Engineering and Engineering Management,* pp. 1352-1356.

Rosenbloom, S. T., Carroll, R. J., Warner, J. L., Matheny, M. E., & Denny, J. C. (2017). Representing knowledge consistently across health systems. *Yearbook of medical informatics*, 26(1), p. 139.

Ross, C., Orr, E. S., Sisic, M., Arsenault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior,* 25(2), pp. 578-586.

Roy, S. K., & Balaji, M. S. (2015). *Measurement and validation of online financial service quality (OFSQ). Marketing Intelligence & Planning*, 33 (7), pp. 1004-1026.

Rudolph, L., Caplan, J., Ben-Moshe, K., & Dillon, L. (2016). *Health in All Policies: A Guide for State and Local Governments*. Washington, DC and Oakland, CA: American Public Health Association and Public Health Institute. [Online]. Available at: http://www.phi.org/uploads/files/Health_in_All_Policies-A_Guide_for_State_and_Local_Governments.pdf [Accessed 16 September 2021].

Rycroft-Malone, J., Burton, C. R., Wilkinson, J., Harvey, G., McCormack, B., Baker, R., & Williams, L. (2016). Collective action for implementation: *A realist evaluation of organisational collaboration in healthcare, Implementation Science*, 11(17). doi 10.1186/s13012-016-0380-z.

Sackett, D., L, Rosenberg, W., M, Gray, J., A, (2018). *Evidence based medicine: what it is and what it is not. BMJ* 1996; 312:71–2. 10.1136/bmj.312.7023.71.

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*, pp. 209–232.

Sahi, A., Lai, D., & Li, Y. (2016). Security and privacy preserving approaches in the eHealth clouds with disaster recovery plan. *Computers in Biology and Medicine*, 78, pp. 1–8, https://doi.org/10.1016/j.compbiomed.2016.09.00 3.

Saigi-Rubió, F., Jiménez-Zarco, A., & Torrent-Sellens, J. (2016). Determinants of the intention to use telemedicine: evidence from primary care physicians. *Int J Technol Assess Health Care* .32(1-2), pp. 29-36.

Salehi, Z., Mokhtar, N. J., Khademolhoseyni, S. M. & Ebadi, A. (2015). 'Effect of education of evidence-based nursing guidelines on the nurses' knowledge in the neonatal intensive care unit', *Iran Journal of Pediatric Nursing*, 1(2), pp. 20-28.

Salvage, J., & White, J., (2019). Nursing leadership and health policy: everybody's business. *Int. Nurs. Rev*. 66 (2), pp. 147–150. doi:10.1111/inr.12523.

Sánchez, R. A., & Hueros, A. D. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in Human Behavior*, 26(6), pp. 1632–1640.

Sanders, (2016). 'Defining terms: Datta, information and knowledge', Proceedings of SAI Computing Conference, London, UK, 13-15 July 2016, pp. 223-228. IEEE viewed 05 August 2020, from https://ieeexplore.ieee.org/document/7555986.

Saripah, Putri., & Darwin. (2016). The Influence of Trust, Benefit Perception, Risk Perceion, and Satisfaction of Taxpayers on the Use of E-Filing for Individuals Taxpayers in KPP Pratama Pekanbaru, Handsome in 2015. *Jurnal Akuntansi Dan Ekoomika,* 6(2). [Indonesian].

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

Saunders, M., Lewis, P., & Thornhill, A. (2019). *Research methods for business students*. (8th Edition). London: Pearson Education.

Schartinger, D., Miles, I, Saritas O, Amantidou E, Giesecke. S., & Heller-Schuh B, et al. (2015). Personal Health Systems Technologies: Critical Issues in Service Innovation and Diffusion. *Technology Innovation Management Review*: pp. 46-56.

Schopf, T. R, Nedrebø, B, Hufthammer, K. O., Daphu, I. K., & Lærum, H. (2019). How well is the electronic health record supporting the clinical tasks of hospital physicians? A survey of physicians at three Norwegian hospitals. *BMC Health Serv Res,* 19(1): pp. 1–9.

Schumacker, R. E., & Lomax, R. G. (2016). *A Beginner's Guide to Structural Equation* Modeling (4th Ed.). New York: Routledge.

Sebetci, Ö. (2018). Enhancing end-user satisfaction through technology compatibility: An assessment on health information system. *Health Policy and Technology*, 7(3), pp. 265-274.

Secginli, S., Erdogan, S., & Monsen, K. A. (2014). Attitudes of health professionals towards electronic health records in primary health care settings: a questionnaire survey. *Informatics for Health & Social Care*, 39(1), pp. 15–32.

Seddon, P. B. (1997). A respecification and extension of the DeLone and McLean model of IS success. *Information systems research*, 8(3), pp. 240-253.

Seddon, P., & Kiew, M. Y. (1996). A partial test and development of DeLone and McLean's model of IS success. *Australasian Journal of Information Systems*, 4(1).

Sedgwick, P. (2014). *Cross sectional studies: advantages and disadvantages.* BMJ, 348. [Online]. Available at: https://doi.org/10.1136/bmj.g2276. [Accessed 16 September 2021].

Segars, A. H., & Grover, V. (1993). Re-examining ease of use and usefulness: A confirmatory factor analysis. *MIS Quarterly,* 17(4), pp. 517–527.

Sekaran, U., & Bougie, R. (2016). *Research Methods for Business: A Skill Building Approach*, (7th Edition). Chichester, United Kingdom: Wiley.

Sellbom, M., & Tellegen, A. (2019). Factor analysis in psychological assessment research: Common pitfalls and recommendations. *Psychological Assessment*, 31(12), pp. 1428–1441.

Shaari, R., Bakri, N., & Rahman, A. A. (2015). ‘Antecedents of knowledge sharing behavior among nurses: Towards research agenda’, *Procedia - Social and Behavioral Sciences*, 171: pp. 635- 641.

Shagari, S. L., Abdullah, A., & Saat, R. M. (2017). Accounting information systems effectiveness: Evidence from the Nigerian banking sector. *Interdisciplinary Journal of Information, Knowledge, and Management,* 12, pp. 309–335. doi:10.28945/3891.

Shaltoni, A. M. (2017). From websites to social media: exploring the adoption of Internet marketing in emerging industrial markets. *Journal of Business & Industrial Marketing,* 32(7), pp. 1009–1019. doi:10.1108/jbim-06-2016-0122.

Shannon-Baker, P. (2016). Making paradigms meaningful in mixed methods research. *Journal of Mixed Methods Research*, *10*(4), pp. 1-16.

Shayan, S. J., Kiwanuka F., & Nakaye, Z. (2019). Barriers Associated with Evidence-Based Practice Among Nurses in Low- and Middle-Income Countries: *A Systematic Review. Worldviews Evid Based Nurs* 16(1), pp. 12–20. DOI: 10.1111/wvn.12337.

Shen, G. (2015). Users’ adoption of mobile applications: Product type and message framing’s moderating effect. *Journal of Business Research,* 68(11), pp.2317–2321.

Shitu, Z., Hassan, I., Aung, M., Kamaruzaman, T., & Musa, R. (2018). *Avoiding medication errors through effective communication in healthcare environment. Movement, Health & Exercise*, 7(1), pp. 113-126.

Shonhe, L. (2017). *Change management practices in the implementation of records management programs: a case study of Tlokweng Land Board. Master's thesis*. Gaborone: University of Botswana.

Shrestha, A. K., & Basnet, N., (2018). The correlation and regression analysis of physicochemical parameters of river water for the evaluation of percentage contribution to electrical conductivity. *Journal of Chemistry.*

Shuaib, W., Suarez, J. M., & Romero. J. D. (2016). Transforming patient care by introducing an electronic medical records initiative in a developing country. *Health Inform J,* 22(4), pp. 975-983.

Shuvo, T. A., Islam, R. Hossain, S, Evans, J., Khatun, F., Ahmed, T., Gazi, R. & Adams, A., M (2015). eHealth Innovations in LMICs of Africa and Asia: A Literature Review Exploring Factors Affecting Implementation, Scale-up, and Sustainability. Innov Entrep Health. 2, pp. 95–106.

Sigerson, L., & Cheng, C. (2018). Scales for measuring user engagement with social network sites: A systematic review of psychometric properties. *Computers in Human Behavior,* 83, pp. 87-105.

Singh, H. (Ed.) (2014). Helping Health Care Organisations to Define Diagnostic Errors as Missed Opportunities in Diagnosis. *Joint Commission Journal on Quality and Patient Safety,* 40(3), pp. 99–101.

Singh, N., & Sinha, N. (2020). How perceived trust mediates merchant's intention to use a mobile wallet technology. *Journal of Retailing and Consumer Services* 52: 101894.

Singh, P., Keswani, S., Singh, S., & Sharma, S. (2016). A Study of Adoption Behavior for Online Shopping: An Extension of Tam Model. *International Journal Advances in Social Science and Humanities.* 4(7), pp. 11-22.

Sittig, D. F., Belmont, E., & Singh, H. (2018). Improving the safety of health information technology requires shared responsibility: *It is time we all step up. In Healthcare*, 6 (1), pp. 7-12. Elsevier.

Siu, H. M. (2015). *Understanding nurses' knowledge work*. DPhil thesis. Western University.

South African Nursing Council. (2019). *Education and Training matters.* https://www.sanc.co.za/wp-content/uploads/2020/08/Education-Training.pdf. (18 June 2019).

Spring, B., & Neville, K. (2014). Evidence-based practice in clinical psychology. In Barlow DH (Ed.), *The Oxford handbook of clinical psychology* (2nd Edition). pp. 128–149). New York: Oxford University Press.

Sriwindono, H., & Tumiwa, F. (2016). *Learning management system success analysis (Case Study*: USD Yogyakarta). Media Techniques, 11(2), pp. 77-82.

Statistisches Bundesamt. (2020) Bruttoinlandsprodukt im 1. *Quartal 2020 um 2,2 % niedriger als im Vorquartal.* Pressemitteilung Nr. 169 vom 15. Mai 2020. Wiesbaden: Statisti- sches Bundesamt.

Stefanou C. J., & Skouras, A. (2015). E-government: Applications in the labor and social security regulatory area. Transforming Government: *People. Process and Policy,* 9(4), pp. 448–464.

Stevens, J. P. (2009). *Applied multivariate statistics for the social sciences* (5th ed.). New York, NY: Taylor & Francis Group.

Stralen, M., Yildirim, M., & te Velde, S. (2019). *Mediation and moderation analyses.* Amsterdam, Netherlands: Vrije Universiteit Amsterdam.

Strudwick, G., Booth, R. G., Bjarnadottir, R. I., Rossetti, S., Friesen, M., Sequeira, L., Munnery, M., & Srivastava, R. (2019). The role of nurse managers in the adoption of health information technology: Findings from a qualitative study. *Journal of Nursing Administration*, 49(11), pp. 549–555.

Sudarto, S., Sufarnap, E., Ulfah, R., & Amalia, C. (2020). Analysis of information system implementation success using the Delon & McLean model. *Paper presented at the Proceedings of the National Seminar on Information Science Research (SENARIS).*

Swedish government (2020). Committee directives. A new law on elder care. Issued 22 December 2020 [Online]. Available at: https://www.regeringen.se/rattsliga-dokument/kommittedirektiv/2020/12/dir.-2020142/ [Accessed 16 September 2021].

Tabachnick, B., & Fidell, L. (2019). *Using Multivariate Statistics. Boston*, MA: Pearson Education Inc.

Tacia, L., Biskupski, K., Pheley, A., & Lehto, R. H. (2015). Identifying barriers to evidence-based practice adoption: *A focus group study. Clinical Nursing Studies*, 3(2), pp. 90-96.

Taherdoost, H. (2018). Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research. *SSRN Electronic Journal*. [Online]. Available at: https://doi.org/10.2139/ssrn.3205040. [Accessed 14 September 2020].

Tall, J. M., Hurd, M., & Gifford, T. (2015). Minimal impact of an electronic medical records system. *The American Journal of Emergency Medicine*, *33*(5), pp. 663–666.

Tallaha, A. M., Shukor, Z. A., & Abu Hassan, N. S. (2014). Factors influencing e-filing usage among Malaysian taxpayers: Does tax knowledge matter? *Jurnal Pengurusan*, 40, pp. 91-101.

Tan, C., Abdaless, S., & Liu, K. (2018). Norm-based abduction process (NAP) in developing information architecture. *IFIP Advances in Information and Communication Technology,* 527, pp. 33–42.

Tang, H. (2017). A study of the effect of knowledge management on organizational culture and organizational effectiveness in medicine and health sciences*. Eurasia Journal of Mathematics, Science and Technology Education,* 13(6), pp. 1831–1845.

Tavares, J., & Oliveira, T. (2017). Electronic health record portal adoption: A cross country analysis. *BMC Medical Informatics and Decision Making,* 17(1), p. 97.

Taylor, S. J., Bogdan, R., & DeVault, M. (2016). *Introduction to Qualitative Research Methods: A Guidebook and Resource* (4th ed.). Hoboken, NJ: John Wiley & Sons Inc.

Taylor, S. P. (2018). Critical realism vs social constructionism & social constructivism: application to a social housing research study. *International Journal of Sciences: Basic and Applied Research*, 37(2), pp. 216-222.

Tetteh, G. K. (2016). State-of-the-art: Research theoretical framework of information systems implementation research in the health sector in sub-Saharan Africa. *Journal of Health Informatics in Developing Countries*, 8.

The Academy of Medical-Surgical Nurses. (2019). *Evidence-based practice.* [Online]. Available at: https://www.amsn.org/practice resources/ evidence-based-practice. [Accessed 19 June 2020].

The Agency for Healthcare Research and Quality. (2018). *Clinical Guidelines and Recommendations.* [Online]. Available at: https://www.ahrq.gov/professionals/clinicians-providers/guidelines-recommendations/index.html. [Accessed 16 August 2020].

The Swedish Institute (2018). *Healthcare in Sweden*. [Online] The Swedish Institute. Available at: https://sweden.se/society/health-care-in-sweden/ [Accessed 16 September 2021].

Thériault G, Bell NR, Grad R, (2019). Teaching shared decision making: an essential competency. *Can Fam Physician*; 65: 514–6.

Thomas, S. (2016). An analysis of the adoption of electronic health records in primary healthcare. *MBA report. Gordon Institution of Business Science,* University of Pretoria.

Tilahun, B., & Fritz, F. (2015). Modeling antecedents of electronic medical record system implementation success in low resource setting hospitals. *BMC Med Inform Decis Mak*. pp.15-61.

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation. Lexington,* Mass: Lexington Books (Issues in organisation and management series).

Tsou, H., & Hsu, S. H. (2015). Performance effects of technology-organisation-environment openness, service co-production, and digital-resource readiness: The case of the IT industry. *International Journal of Information Management*, 35(1), pp. 1-14.

Turyahikayo, E. (2021). Philosophical paradigms as the bases for knowledge management research and practice. Knowledge Management & E-Learning, 13(2), pp. 209–224.

Udo, G. J., Bagchi, K. K., & Kirs, P. J. (2012). Exploring the role of espoused values on eservice adoption: A comparative analysis of the US and Nigerian users. *Computers in Human Behavior,* 28(5), pp. 1768–1781.

Uluc, N. C., & Ferman, M. (2016). A comparative analysis of user insights for e-health development challenges in Turkey, Kingdom of Saudi Arabia, Egypt and United Arab Emirates: *Journal of Management and Logistics;* 3(2), pp. 176–18.

Umezuruike, C., Okolie, S. O., Adebayo, A. O., Nwankwo, W., & Jonah, J. V. (2017). Developing an informatics model for effective healthcare inmilitaryhealthfacilitiesinNigeria: *World Journal of Engineering Research and Technology;* 3(5), pp. 69-99.

URT. (2016). *The National Five-Year Development Plan 2016/17 – 2020/2*1 United Republic of Tanzania. p. 316.

Van der Gaag, M. A. E., De Ruiter, N. M. P., & Kunnen, E. S. (2016). Micro-level processes of identity development: Intra-individual relations between commitment and exploration. *Journal of Adolescence,* 47, pp. 38-47.

van der Vaart, R., Drossaert, C. H., Taal, E., Drossaers-Baker, K. W., Vonkeman, H. E., & van de Laar, M. A. (2014). Impact of patient-accessible electronic medical records in rheumatology: Use, satisfaction, and effects on empowerment among patients. *BMC Musculoskeletal Disorders,* 15, 102. doi:10.1186/1471-2474-15- 102.

Van Hoeven, L. R., De Bruijne, M. C., Kemper, P. F., Koopman, M. M., Rondeel, J. M., Leyte, A., & Roes, K. C. (2017). Validation of multisource electronic health record data: an application to blood transfusion data. *BMC medical informatics and decision-making*, 17(1), p.107.

Van Zyl, E. (2014). The role of self-leadership in becoming an ethical leader in the South African work context. *African Journal of Business Ethics*, 8(2). [Online]. Available at: https://doi.org/10.15249/8-2-82. [Accessed 18 May 2020].

Varpio, L, Paradis, E, Uijtdehaage, S., & Young, M, (2020). 'The Distinctions Between Theory, Theoretical Framework, and Conceptual Framework', *Academic Medicine*, 95(7), pp. 989–994.

Vélez, O., Okyere, P. B., Kanter, A. S., & Bakken, S. (2014). A usability study of a mobile health application for rural Ghanaian midwives. *Journal of Midwifery and Women's Health,* 59(2), pp. 184–191. [Online]. Available at: https://doi.org/10.1111/jmwh.12071. [Accessed 16 September 2021].

Venkatesh, Thong., & Xu, (2016). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly,* p.361, 157.

Venkatesh, V., Davis, F. D., Venkatesh, V., & Davis, F. D. (2016). A theoretical extension of the technology acceptance model. *Four Longitudinal Field Studies.* 46(2), pp. 186–204.

Vessey, I., & Ward, K. (2013). The dynamics of sustainable IS alignment: The case for IS adaptively. *Journal of the Association for Information Systems*, 14, pp. 283-311.

Vieira, E. T. (2017). *Introduction to real world statistics: With step-by-step SPSS instructions.* New York: Routledge.

Vogelsmeier, A. A., Halbesleben, J. R. B., & Scott-Cawiezell, J. R. (2016). Technology Implementation and Workarounds in the Nursing Home. *Journal of the American Medical Informatics Association,* 15(1), pp. 114–119.

Vos, J., Boonstra, A., Kooistra, A., Seelen, M. A. J., & Offenbeek, van, M. (2020). *Facilitating and constraining influences of an Electronic Health Record on collaboration among medical specialties*. Paper presented at EHMA. *Annual Conference, Rotterdam, Netherlands.*

Wade, V., Gray, L., & Carati, C. (2016). Theoretical frameworks in telemedicine research. *Journal of Telemedicine and Telecare,* 23(1), pp. 181–187.

Waehama, W., McGrath, M., Korthaus, A., & Fong, M. (2014). ICT Adoption and the UTAUT Model. P*aper presented at the International Conference on Educational Technology Information Technology (ICETIS2014),* Bangkok, Thailand.

Wager, K. A., Lee, F. W., & Glaser, J. P., (2017). Health care information systems: *a practical approach for health care management.* John Wiley & Sons.

Wang, F., & Preininger, A. (2019). AI in health: State of the art, challenges, and future directions. *Yearbook of Medical Informatics*, 28, pp. 16–26.

Wang, Y. S. (2016). Assessing e-commerce systems success: a respecification and validation of the DeLone and McLean model of IS success. *Information systems journal,* 18(5), pp. 529-557.

Wani, D., & Malhotra, M. (2018). Does the meaningful use of electronic health records improve patient outcomes? *Journal of Operations Management*, *60*(1), pp. 1–18.

Warren, J., McLaughlin, M., Bardsley, J., Eich, J., Esche, C., Kropkowski, L., & Risch, S. (2016). *The strengths and challenges of implementing EBP in healthcare systems. Worldviews on Evidence Based Nursing,* 13(1), pp. 15-24.

Webster, P. C. (2011). Experts call for health infoway “watchdog.”*CMAJ: Canadian Medical Association Journal, 183*(3), pp. 298–299. [Online]. Available at: https://doi.org/10.1503/cmaj.109-3783. [Accessed 16 September 2021].

Western Cape Government. (2016). *New Patient Administrative (AR) and Billing system at Prince Albert Hospital.*

WHO, (2018). *Low quality healthcare is increasing the burden of illness and health costs globally.* [Online]. Available at: https://www.who.int/newsroom/detail/05-07-2018-low-quality-healthcare-is-increasing-the-burden-of-illness-andhealth-costs-globally. [Accessed 16 September 2021].

Wickramasinghe, N. S., Fadlalla, A. M. A., Geisler, E., & Schaffer, J. L. (2015). A framework for assessing eHealth preparedness. *International journal of electronic healthcare,* 1(3), pp. 316– 334.

Wiedenhöfer, D., & Keppler, S. (2014). Free hospital choice in Switzerland - patients' decision criteria and sources of information. *Interdiscip Manag Res.*10: pp. 763–73.

Willis, E., & Parry, Y. (2016). The Australian health care system. In: Willis E, Reynolds L, Keleher H. *Understanding the Australian Health Care System*. Chatswood, NSW, Australia: Elsevier, pp. 232-277.

Wisdom, J. P. Chor, K. H. B., Hoagwood, K. E., & Horwitz, S. M. J. A. (2014). Innovation adoption: A review of theories and constructs. *Adm. Policy Ment. Health Ment. Health Serv. Res.* 41, pp. 480–502.

World Health Organisation. (2022). *South Africa: WHO coronavirus disease (COVID-19) dashboard with vaccination data.* [Online]. Available at: https://covid19.who.int. [Accessed 16 September 2021].

World Health Organisation. (2017). Health systems. [Online]. Available at: http://www.who.int/healthsystems/about/en/ [Accessed 18 September 2021].

Wright, G., O 'Mahony, D., & L. Cilliers, L. (2017). "Electronic Health Information Systems for Public Health Care in South Africa: A Review of Current Operational Systems." J*ournal of Health Informatics in Africa 4* (1): pp. 51–57.

Xu, W. Ou, P., & Fan, W. (2017). Antecedents of ERP assimilation and its impact on ERP value: A TOE-based model and empirical test. *Inf. Syst. Front. 19*, pp. 13–30.

Yazdi-Feyzabadi, V., Emami, M., & Mehrolhassani, M. H. (2015). Health information system in primary health care: the challenges and barriers from local providers' perspective of an area in Iran. *Int J Prev Med*. pp. 6-57.

Yeow, A, Soh C., & Hansen, R. (2018) Aligning with new digital strategy: a dynamic capabilities approach. *J Strateg Inf Syst 27*(1): pp.43–58.

Yin, R. K. (2017). *Case study research and applications: Design and methods.* Thousand Oaks, CA: Sage.

Ying, H., & Lee, S. (2016). 'Survey of the research of ICT applications in the AEC industry: A view from two mainstream journals', in *Proceedings of the 16th International Conference on Construction Applications of Virtual Reality,* The Hong Kong University of Science and Technology, Hong Kong, December 11–13, pp. 471–483.

Yingfeng, Z. et al. (2020). Studies on evidence implementation in clinical nursing practice in China: A Scoping Review. *Chinese Nursing Management.*2020; 20, pp. 513-518.

Yoon, D., Chang, B. C., Kang, S. W., Bae, H., & Park, R. W. (2014). Adoption of electronic health records in Korean tertiary teaching and general hospitals. *Int J Med Inform.* 81, pp. 196– 203.

Yoon, S., & Cho, E. (2016). Convergence adoption model (CAM) in the context of a smart car service. *Computers in Human Behavior* .60, pp. 500–507.

You, H., S. (2015) Do Schools Make a Difference? Exploring School Effects on Mathematics Achievement in PISA 2012 Using Hierarchical Linear Modeling. *J. Educ. Eval.* 28, pp. 1301–1327.

Young, M. (2016). *'Private vs. public healthcare in South Africa'*, Honors thesis, Western Michigan University.

Yu, L., & Shek, D. T. L. (2014). Testing factorial invariance across groups: An illustration using AMOS. *International Journal on Disability and Human Development*, 13(2), pp. 205–216.

Yuan, K. H., Chan W., Marcoulides, G. A., & Bentler P. M. (2016). Assessing structural equation models by equivalence testing with adjusted fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(3), pp. 319-330.

Zarei, E., Daneshkohan, A, Pouragha, B., Marzban, S., & Arab, M. (2014). An empirical study of the impact of service quality on patient satisfaction in private hospitals. *Iran Glob J Health.*7(1): p.1.

Zayyad, M. A., & Toycan, M. (2018). Factors affecting sustainable adoption of e-health technology in developing countries: An exploratory survey of Nigerian hospitals from the perspective of healthcare professionals. *PeerJ* 6: e4436; DOI 10.7717/peerj.4436.

Zeng, X. (2016). The impacts of electronic health record implementation on the health care workforce. *N C Med J,* 77(2), pp. pp. 112–114.

Zhang, S, Zhang, C., & Yang, Q. (2003). Data preparation for data mining. *Appl Artif Intell* 17: pp. 375–381.

Zhang, X., Han, X., Dang, Y., Meng, F., Guo, X., & Lin, J. (2017). User acceptance of mobile health services from users- perspectives: The role of self-efficacy and response-efficacy in technology acceptance. *Informatics for Health and Social Care*, 42(2), pp. 194-206.

Zhang, Y., Sun, J., Yang, Z., & Wang, Y. (2020). Critical success factors of green innovation: Technology, organisation, and environment readiness. *J. Clean. Prod*. 264, 121701. doi: 10.1016/j.jclepro.2020.121701.

Zhao J. et al. (2017). Exploring on nursing educational innovation with best practice guidelines to cultivate evidence-informed practice**.** *J Nurs Educ Pract.* 7: pp. 6.

Zhou, L., Zhang, D., Yang, C. C., & Wang, Y. (2018). Harnessing social media for health information management. *Electronic Commerce Research and Applications*, 27, pp. 139–151. Doi:10.1016/j. elerap.2017.12.003 PMID:30147636.

Zikmund, W. G., Babin, B. J., Carr, J. C., & Griffin, M. (2013). *Business Research Methods.* Ninth Edition. Canada: Cengage Learning.

Zolfagharian, M., Romme, A. G. L., & Walrave, B., (2018). Why, when, and how to combine system dynamics with other methods: *towards an evidence-based framework*. J. Simulation 12(2), pp. 1–17.

Žukauskas, P., Vveinhardt, J., & Andriukaitienė, R. (2018). Philosophy and paradigm of scientific research. In P. Žukauskas, J. Vveinhardt, & R. P. Andriukaitienė (Eds.), Management Culture and Corporate Social Responsibility. pp. 121-138. London: OpenTech.

APPENDIX 1: ETHICAL APPROVAL

UNISA university of south africa

UNISA-CAES HEALTH RESEARCH ETHICS COMMITTEE

Date: 09/09/2019

Dear Dr Motsi

NHREC Registration # : REC-170616-051
REC Reference # : 2019/CAES/075
Name : Dr L Motsi
Student #: 31861113

Decision: Ethics Approval from 05/09/2019 to completion

Researcher(s): Dr L Motsi
motsil@unisa.ac.za

Supervisor (s): Prof A Coleman
colema@unisa.ac.za; 011-670-9108

Dr B Chimbo
chimbb@unisa.ac.za; 011-670-9105

Working title of research:
Framing critical success factors for evidence-based healthcare practice in South Africa public hospitals

Qualification: PhD Computing

Thank you for the application for research ethics clearance by the Unisa-CAES Health Research Ethics Committee for the above mentioned research. Ethics approval is granted until the completion of the project, **subject to submission of yearly progress reports. Failure to submit the progress report will lead to withdrawal of the ethics clearance until the report has been submitted.**

Due date for progress report: 31 August 2020

*The **low risk application** was **reviewed** by the UNISA-CAES Health Research Ethics Committee on 05 September 2019 in compliance with the Unisa Policy on Research Ethics and the Standard Operating Procedure on Research Ethics Risk Assessment.*

The proposed research may now commence with the provisions that:

Open Rubric

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1. The researcher(s) will ensure that the research project adheres to the values and principles expressed in the UNISA Policy on Research Ethics.
2. Any adverse circumstance arising in the undertaking of the research project that is relevant to the ethicality of the study should be communicated in writing to the Committee.
3. The researcher(s) will conduct the study according to the methods and procedures set out in the approved application.
4. Any changes that can affect the study-related risks for the research participants, particularly in terms of assurances made with regards to the protection of participants' privacy and the confidentiality of the data, should be reported to the Committee in writing, accompanied by a progress report.
5. The researcher will ensure that the research project adheres to any applicable national legislation, professional codes of conduct, institutional guidelines and scientific standards relevant to the specific field of study. Adherence to the following South African legislation is important, if applicable: Protection of Personal Information Act, no 4 of 2013; Children's act no 38 of 2005 and the National Health Act, no 61 of 2003.
6. Only de-identified research data may be used for secondary research purposes in future on condition that the research objectives are similar to those of the original research. Secondary use of identifiable human research data require additional ethics clearance.
7. No field work activities may continue after the expiry date. Submission of a completed research ethics progress report will constitute an application for renewal of Ethics Research Committee approval.

Note:
*The reference number **2019/CAES/075** should be clearly indicated on all forms of communication with the intended research participants, as well as with the Committee.*

Yours sincerely,

Prof MA Antwi
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APPENDIX 2: PARTICIPANT INFORMATION SHEET

UNISA university of south africa

Ethics clearance reference number: 2019/CAES/075
Research permission reference number (if applicable):

22nd of March 2019

Dear Prospective Participant

My name is Lovemore Motsi, and I am a doctoral student in information systems at the University of South Africa. I am conducting research under the supervision of Prof. Bester Chimbo in the School of Computing. We are inviting you to participate in a study entitled: **Modeling of critical success for evidence-based healthcare practice at a South African public hospital.**

WHAT IS THE PURPOSE OF THE STUDY?

I am conducting this research to determine the critical success factors that will influence the adoption of evidence-based healthcare practice at a South African public hospital.

WHY AM I BEING INVITED TO PARTICIPATE?

Since you are part of healthcare professionals (medical doctors, nurses, pharmacists, radiologists and radiographers), your participation will greatly assist in this research. You have been selected randomly, from a population of entrepreneurs. The total number of participants that will take part in this research is 300.

WHAT IS THE PURPOSE OF THE STUDY?

I am conducting this research to determine the critical success factors that will influence the adoption of evidence-based healthcare practice at a South African public hospital.

WHY AM I BEING INVITED TO PARTICIPATE?

Since you are part of healthcare professionals (medical doctors, nurses, pharmacists, radiologists and radiographers), your participation will greatly assist in this research. You have been selected randomly, from a population of entrepreneurs. The total number of participants that will take part in this research is 300.

WHAT IS THE NATURE OF MY PARTICIPATION IN THIS STUDY?

This quantitative study questionnaire study involves surveys. Questions related to critical success factors for the adoption and implementation of Electronic Health Records (EHR) and factors that influence the adoption and implementation of EHR. A conceptual framework for the

CAN I WITHDRAW FROM THIS STUDY EVEN AFTER HAVING AGREED TO PARTICIPATE?

Participating in this study is voluntary and you are under no obligation to consent to participation. If you do decide to take part, you will be given this information sheet to keep and be asked to sign a written consent form. You are free to withdraw at any time and without giving a reason.

WHAT ARE THE POTENTIAL BENEFITS OF TAKING PART IN THIS STUDY?

No monetary gifts or any other gifts will be given for taking party in this study. However, as a participant, you will learn a lot on the benefits of using EHRs in South Africa public hospitals.

ARE THERE ANY NEGATIVE CONSEQUENCES FOR ME IF I PARTICIPATE IN THE RESEARCH PROJECT?

If you have a very busy schedule, time to participate may be the only problem, but as stated before, the survey will only take 20 minutes to complete.

WILL THE INFORMATION THAT I CONVEY TO THE RESEARCHER AND MY IDENTITY BE KEPT CONFIDENTIAL?

Your name will not be recorded anywhere and your participation in this research will be kept private by the researcher. No one will be able to connect you to the answers you give. Your answers will be given a code number or a pseudonym and you will be referred to in this way in the data, any publications, or other research reporting methods such as conference proceedings.

Your anonymous data may be used for other purposes, such as a research report, journal articles and/or conference proceedings. Privacy will be protected in any publication of the information as you will not be identifiable in such a report.

HOW WILL THE RESEARCHER(S) PROTECT THE SECURITY OF DATA?

Hard copies of your answers will be stored by the researcher for a minimum period of five years in a locked cupboard/filing cabinet for future research or academic purposes; electronic information will be stored on a password protected computer. Future use of the stored data will be subject to further Research Ethics Review and approval if applicable. Hard copies will be shredded and/or electronic copies will be permanently deleted from the hard drive of the computer.

WILL I RECEIVE PAYMENT OR ANY INCENTIVES FOR PARTICIPATING IN THIS STUDY?

There will be no payment or incentives offered for participant, though you will gain valuable knowledge in participating. Participation is voluntary. No costs will be incurred by you.

HAS THE STUDY RECEIVED ETHICS APPROVAL

This study has received written approval from the Research Ethics Review Committee of the School of Computing, Unisa. A copy of the approval letter can be obtained from the researcher if you so wish.

HOW WILL I BE INFORMED OF THE FINDINGS/RESULTS OF THE RESEARCH?

If you would like to be informed of the final research findings, please contact Dr L.Motsi on 0614666500 or 31861113@mylife.unisa.ac.za. The findings are accessible for 1 year.

Should you require any further information or want to contact the researcher about any aspect of this study, please contact Dr L. Motsi on 0614666500 or 31861113@mylife.unisa.ac.za.

Should you have concerns about the way in which the research has been conducted, you may contact Prof B. Chimbo on 011 670 9105 or chimbb@unisa.ac.za. Contact the research ethics chairperson of the School of Computing, Unisa, if you have any ethical concerns.

Thank you for taking time to read this information sheet and for participating in this study.

Lovemore Motsi

APPENDIX 3: CONSENT TO PARTICIPANT IN THIS STUDY

UNISA university of south africa

I, _________________ (participant name), confirm that the person asking my consent to take part in this research has told me about the nature, procedure, potential benefits and anticipated inconvenience of participation. I have read (or had explained to me) and understood the study as explained in the information sheet.

I have had sufficient opportunity to ask questions and am prepared to participate in the study. I understand that my participation is voluntary and that I am free to withdraw at any time without penalty (if applicable).

I am aware that the findings of this study will be processed into a research report, journal publications and/or conference proceedings, but that my participation will be kept confidential unless otherwise specified.

I agree to the recording of the survey data collection method.

I have received a signed copy of the informed consent agreement.

Participant Name & Surname………………………………………… (please print)

Participant Signature…………………………………………Date…………………

Researcher's Name & Surname……Lovemore Motsi……………(please print)

Researcher's signature…… ……………………..Date……25/03/2019……

University of South Africa
Preller Street, Muckleneuk Ridge, City of Tshwane

APPENDIX 4: LETTER OF APPROVAL

GAUTENG PROVINCE
HEALTH
REPUBLIC OF SOUTH AFRICA

Dr. George Mukhari Academic Hospital

Office of the Director Clinical Services
Enquiries : Dr. C Holm
Tel : (012) 529 3691
Fax : (012) 560 0099
Email:Christene.Holm @gauteng.go.za
keitumetse.mongale@gauteng.gov.za

To Dr L MOTSI
Department of Science and Engineering (CSET)
University of South Africa

Date : 10 October 2019

PERMISSION TO CONDUCT RESEARCH

The Dr George Mukhari Academic Hospital hereby grants you permission to conduct research on "Framing critical success factors for evidence-based healthcare practice in South Africa public hospitals" at Dr George Mukhari Academic Hospital".

This permission is granted subject to the following conditions:

- ☑ That you obtain Ethical Clearance from the Human Research Ethics Committee of the relevant University
- ☑ That the Hospital incurs no cost in the course of your research
- ☑ That access to the staff and patients at the Dr George Mukhari Hospital will not interrupt the daily provision of services.
- ☑ That prior to conducting the research you will liaise with the supervisors of the relevant sections to introduce yourself (with this letter) and to make arrangements with them in a manner that is convenient to the sections.
- ☑ Formal written feedback on research outcomes must be given to the Director: Clinical Services
- ☑ Permission for publication of research must be obtained from the Chief Executive Officer

Yours sincerely

DR. C. HOLM
ACTING DIRECTOR CLINICAL SERVICES
DATE: 10/10/19

APPENDIX 5: QUESTIONNAIRE

Questionnaire: Framing Critical Success Factors for Evidence-Based Healthcare Practice: A Study of Public Hospitals in South Africa

Please select the applicable by placing an X in the box next to it.

SECTION A: GENERAL INFORMATION

1. What is your Gender

Female		Male	

2. Age Group

20 yrs and below		31 – 35 yrs	
21 – 25 yrs		36 – 40 yrs	
26 – 30 yrs		41 Yrs	

3. What is your highest education level?

High School		Masters	
Certificate		Doctorate (PhD)	
Diploma		Other (please specify)	
Bachelors ‘Degree			
MBCHB			

4. Which of the following hospital/clinic are you currently working?

Steve Biko Academic Hospital		Chris Hani Baragwnath Hospital	
George Muhari Academic Hospital		Charlotte Maxeke Hospital	

5. What is your position at work?

Medical doctor		Nurse	
Pharmacist		Radiographer	
Radiologist		Dentist	
Physiotherapists		Other (please specify)	
Medical Lab Technologist			

SECTION B: USE OF ELECTRON HEALTH RECORD SYSTEM

Please select the applicable by placing an X in the box next to it.

1. The respondents were asked about the availability of information systems in their specific hospital departments.

Does your hospital have information systems (IS)?	
No	
Yes	
Not sure	

2. The respondents were asked to indicate the importance of information systems in their specific hospital departments.

Importance of information systems (IS)?	
Not important	
Important	
Very important	
Extremely important	

3. Which of the following functions would you propose on an EHR system?

Nurse tasks		Pharmacy task	
Patient admission task		Other (please specify)	
Billing and financial task			
Administrative task			
Laboratory task			

SECTION C: CRITICAL SUCCESS FOR EFFECTIVE IMPLEMENATATION OF EVIDENCE-BASED HEALTHCARE PRACTICE Please select the most appropriate statement by placing an X in the box. Consider the following categories: 1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5= Strongly Agree.						
a): Electronic Health Records		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I am certain that, the EHR system reports will be easier to generate.					
2.	I believe generated reports from EHR system will be accurate.					
3.	I believe it will take a short time to generate a report using EHR system.					
4.	I will accept as true that, EHR system will enable faster patient communication and delivery of care.					
5.	I believe the EMR system will increase data security and confidentiality.					
6.	EMR system will enable the capturing of demographic and clinical health information.					
b): Medical Error Reduction		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I am certain that, using EHR system will reduce errors found within personal health records.					
2.	I believe using EHR system will improve patient management by reducing medical errors.					
3.	I believe using EHR system will provide up-to-date information about the patient.					
4.	I believe using EHR system will provide the medical healthcare professionals with the ability to share patient data.					
5.	I believe using EHR system will provide sufficient information about patient's well-being.					
6.	I will accept as true that, using EHR system will solve the problem of illegible handwriting of health care providers.					
c): Diagnosis and Treatment of Diseases		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I will accept as true that, using EHR system have the capabilities to improve accuracy of patient data, hence fewer errors.					
2.	I believe using EHR system will decrease healthcare professionals' time per patient encounter.					
3.	I am certain that, using EHR system will provide rapid access to patient data as compared to paper-based record system.					
4.	I believe using HER system will improve accuracy of clinical documentation					
5.	I believe using EHR system will enable evidence-based decision making from assigned medical professionals.					
6.	I believe using EHR system will shorten patient waiting time.					

d): Better Coordination of Patient Care		1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
1.	I'm certain that, using EHR system will give me useful reminders that will help me to identify the change of care needs for my patients in a timely manner.					
2.	I believe using EHR system will enable the medical healthcare professionals and other health care providers to make sound clinical decisions in a timely manner.					
3.	I will accept as true that, using EHR system will enable patients to consult other medical healthcare professionals more easily.					
4.	I believe using EHR system will reduce unnecessary patient transfers or referrals to other healthcare providers.					
5.	I'm certain that, using EHR system will reduce patient's cost of health services.					
6.	I believe using HER system will facilitate better patient care when it comes to decision-making.					
e): Information Quality		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe using EHR system will provide patient accurate and up-to-date information					
2.	I will accept as true that, using EHR system will provide information from the system that will be relevant to my work.					
3.	I'm certain that, using EHR system, the information I will get from the system will be accurate.					
4.	I believe using EHR system it will be easy to understand patient information derived from the system.					
5.	I believe using EHR system, the information will be presented in a useful format.					
6.	I believe using EHR system, will enable medical healthcare to share patients records that will enhance information quality.					
f): Knowledge Quality		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I will accept as true that, using EHR system, will ensure that the healthcare professionals have knowledge base necessary to understand the patient condition.					
2.	I am certain that, using EHR system will enable the facilitation of better patient care decision-making.					
3.	I believe using EHR system will ensure that scarce expertise are widely disseminated					

4.	I believe using EHR system, the sheer volumes of data will improve the treatment quality, since it will be easily shared among medical healthcare professionals.					
5.	I'm certain that, using EHR system will accelerate delivery times for patients.					
6.	I believe using EHR system will communicate widely and quickly important information.					
g): Service Quality		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe using EHR system, the support services for the system will be dependable.					
2.	I believe using EHR system, the support services will give me patient individual attention.					
3.	I believe using EHR system will overall, the support services meet my needs.					
4.	I'm certain that, using EHR system will provide more rapid access to patient data than paper-based records.					
5.	I believe using EMR system will be useful in managing patient care in my practice.					
6.	I believe using EHR system will improve service productivity of healthcare professionals.					
a) Perceived Usefulness		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe using EHR system would be useful in my professional activities.					
2.	I believe using EHR system would help improve my patient care delivery.					
3.	I believe the using EHR system would improve my job performance.					
4.	I'm certain that, using EHR system will make health information sharing easier and more effective.					
5.	In my hospital, I believe using EHR system will enable improved coordinated care between medical healthcare professionals.					
6.	In my hospital, I believe using EHR system will reduce medical errors.					
b) Perceived Ease of Use		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe that EHR system has the potential to improve healthcare profession's diagnostic endeavours.					
2.	I believe the use of EHR system will make information dissemination more efficient.					
3.	I'm certain that, it will be easy for me to become skillful in using the EMR system.					
4.	I believe using EHR system will make it easier to adhere to hospital policies such as patient care documentation.					

5.	I believe HER system will increase my diagnosis accuracy.					
6.	I believe in a short period of time I will be an expert in using the EMR system.					
a) Technological Context		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe EMR system will provide electronic records for patients' as well as demographic related information					
2.	I will accept as true that, EMR system will provide electronic records for patient assessment /clinical notes.					
3.	I believe EMR system will provide electronic records for patient financial and fee related information.					
4.	I'm certain that, EMR system will enable the electronic ordering of laboratory tests.					
5.	I believe EMR system will provide electronic ordering of imaging tests (i.e. X-rays, CT scans, MRI scans, etc.)					
6.	I believe EMR system will provide practice administration information systems (i.e. appointment booking/patient scheduling systems).					
b) Organisational Context		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe with the support of top management and the department of health; HER system can be implemented in our public hospitals.					
2.	I believe our top management will make an effort to convince other healthcare professionals of the benefits of EHR system.					
3.	I believe our top management will encourage other healthcare professionals to use EHR system.					
4.	I'm certain that, our medical healthcare institution has the technological resources required to make use of EHR system.					
5.	I believe that, public hospitals have the managerial resources to manage and support the use of EHR system.					
6.	I believe the department of health has the financial resources to make use of EHR system in our public hospitals.					
c) Environmental Context		**1 Strongly disagree**	**2 Disagree**	**3 Neutral**	**4 Agree**	**5 Strongly Agree**
1.	I believe some of our healthcare professionals who are aware of the benefits of the HER system will be happy to see its implementation in our public hospitals.					
2.	I believe the government should be in the forefront in driving the use of EHR system in our public hospitals.					

3.	I believe government should demonstrate a strong commitment to promote the use of EHR system.					
4.	I believe there are effective laws (e.g. with regard to privacy of patient information) that support EHR system.					
5.	I will accept as true that, healthcare professionals should have a strong influence on the EHR system when implemented.					
6.	I believe relationships with our patients will continue to suffer if we do not implement EHR system.					

EVIDANCE-BASED HEALTHCARE PRACTICE
For each outcome listed below, indicate whether you think the effect of EHR system is: Please select the most appropriate statement by placing an X in the box. Consider the following categories: 1 = Strongly disagree 2 = Disagree 3 = Neutral 4 = Agree 5= Strongly Agree.

Effects of EMR System on:	1 Strongly disagree	2 Disagree	3 Neutral	4 Agree	5 Strongly Agree
1. I believe the use of EHR system will enable the reduction healthcare costs.					
2. I believe the use of EHR system will facilitate the interactions with the medical healthcare professional team.					
3. I accept as true that, the use EHR system will allow healthcare professionals to have easy access to patient medical records.					
4. I believe the use of EHR system will be efficient in providing excellent healthcare service.					
5. I believe the use of EHR system will result in the reduction in medical errors.					

Thank you for your support.