TECHNOLOGY ATTRIBUTES, ORGANIZATIONAL LEARNING ATTRIBUTES, SERVICE ATTRIBUTES, AND ELECTRONIC HEALTH RECORD IMPLEMENTATION SUCCESS

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ABSTRACT

Electronic Health Record (EHR) is a technology innovation which has the potential to offer valuable benefits to the healthcare industry such as improved quality of patient care and safety, optimization of healthcare workflow processes and availability of electronic data for clinical research. The implementation success of EHR is therefore significant to the healthcare industry in the United States and around the world. Prior studies in research literature have considered the impact of technology attributes, organizational learning attributes, and service attributes on information technology implementations in various other domains based on theories such as Theory of Reasoned Action (TRA), Theory of Planned Behavior (TRB) and Technology Acceptance Model (TAM), but none have considered their association with implementation success in a comprehensive manner within a single study pertaining to the healthcare domain as this study does. Hence, this study addresses an essential research gap. The approach used by this study in conducting the research based on a multi-factor research model (including the aforementioned attributes) is consistent with the general method used by academic researchers whereby the ability of a unique and selective list of factors to predict certain outcomes is leveraged. The data for this research study was collected using a questionnaire survey instrument based on the Likert scale. Structural Equation Modeling (SEM) was used for data analysis due to the presence of latent variables in the research model. The results of the statistical analyses support the hypotheses confirming positive associations between technology attributes (ease of use, result demonstrability, performance expectancy), organizational learning attributes (organizational learning capability, organizational absorptive capacity), service attributes (service-dominant orientation), and EHR implementation success. The results of this study are of importance to both academicians and practitioners.

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CHAPTER 1

INTRODUCTION

Health Information Technology (HIT) in general, and Electronic Medical Records (EMR) and Electronic Health Records (EHR) in particular have the ability to make a significant impact on public health improvement, healthcare quality enhancement, and healthcare cost containment. The Health Information Technology for Economic and Clinical Health act (HITECH) enacted in 2009 as part of the American Recovery and Reinvestment Act specifies the adoption and meaningful use of health information technology (HIT) to improve health care quality, affordability, and outcomes. In 2011, the Center for Medicaid and Medicare services (CMS) established the EHR incentive program to encourage eligible professionals and hospitals to adopt, upgrade and demonstrate meaningful use of certified EHR technology in three stages. Healthcare providers have adopted EHR over the last few years on a large scale, but there continue to be unsuccessful or partially successful implementations around the world. Barriers to successful implementation of HIT in general and EMR/EHR in particular have been documented in research literature. Uncovering factors impacting successful implementations of HIT in general EMR/EHR in particular will reduce or eliminate unsuccessful implementations and allow the healthcare industry and the public to derive the benefits of such HIT.

The benefits expected to be accrued through the implementation of EHR could be broadly classified into three areas – improved quality of patient care and patient safety, enhanced healthcare provider revenues and optimization of workflows such as billing, and societal benefits including contribution of electronic data to the clinical research community and improved stakeholder satisfaction (Wager, Lee, & Glaser, 2009). Successful implementation of EHR has become vital because it is only when EHR is successfully implemented can the expected benefits be realized. This research study seeks to explore the role of technological, organizational learning and service attributes in successful EHR implementations. This chapter discusses the contextual background using current research literature, states the problem definition and purpose of this study, explains the significance, presents the proposed research model, and the data collection methodology.

Background

Health Information Technology Innovation Perspective

Technology and innovation enable transformation of business processes, enhance organizational productivity, and facilitate collaboration across organizational boundaries (McCardle, 1985; Peng, Dey, & Lahiri, 2014; Sambamurthy & Zmud, 1999). Rogers (2003) defined innovation as “an idea, practice, or project that is perceived as new by an individual or other unit of adoption” (p. 12). Rogers viewed technology as “a design for instrumental action that reduces the uncertainty in the cause-effect relationships involved in achieving a desired outcome” (p. 12).

The United States department of Health and Human Services defines HIT as “the application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of health care information, data, and knowledge for communication and decision making” (Thompson & Brailer, 2004, p. 38). The United States agency for healthcare research and quality (AHRQ) defines innovation in the healthcare context as “the implementation of new or altered products, services, processes, systems, policies, organizational structures, or business models that aim to improve one or more domains of health care quality or reduce health care disparities” (“About the AHRQ Health Care Innovations Exchange”, n.d., para 1). Based on the definitions above, technologies such as telemedicine, computerized provider order entry (CPOE), clinical decision support (CDS), EHRs and mHealth are referred to as HIT innovations in research literature (Labrique et al., 2013; Serova & Guryeva, 2018).

Electronic Health Record as a Health Information Technology Innovation

Patient medical records are used by healthcare organizations for documenting patient care, as a communication tool for all stakeholders involved in the patient’s care, and also to support medical reimbursement and research (Wager, Lee, & Glaser, 2009). To provide holistic health care and evidence-based healthcare, it is imperative to access patient records quickly, easily and universally which makes EMR/EHR a useful tool. In 2008, the National Alliance for Health Information Technology proposed a definition of EHR as “an electronic record of health-related information on an individual that conforms to nationally recognized interoperability standards and that can be created, management and consulted by authorized clinicians and staff across more than one health care organization” (“The National Alliance for Health Information Technology report to the Office of the National Coordinator for Health Information Technology on Defining Key Health Information Technology Terms”, 2008, p. 15). Likewise, the definition of EMR was proposed as “an electronic record of health-related information on an individual that can be created, gathered, managed, and consulted by authorized clinicians and staff if one health care organization” (“The National Alliance for Health Information Technology report to the

Office of the National Coordinator for Health Information Technology on Defining Key Health Information Technology Terms", 2008, p. 15).

The United States office of national coordinator for health information technology (ONC) makes the distinctions that EMRs are a digital version of paper charts in the clinician's office, while EHRs go beyond clinical data by being inclusive of a broader view of patient's care (Garrett & Seidman, 2011). The terms EMR and EHR have been interchangeably used in research literature and practitioner literature alike and are hence used interchangeably in this research study as well. The Institute of Medicine (IOM) calls for eight functions of EHRs including health information and data, results management, order entry and support, decision support, electronic communication and connectivity, patient support, and reporting and population health management.

By passing the HITECH Act, the United States Congress sought to catalyze the use of HIT to improve the quality and efficiency of health care in the United States (Abbett et al., 2011). The meaningful use (MU) provision of the act specifically called for healthcare providers to adopt EHRs to achieve significant improvements in the quality of care. The legislation provided for substantial financial incentives (of approximately $27 billion) to eligible healthcare providers that met MU objectives (Abbett et al., 2011). This fueled both competition and innovation among EHR vendors and healthcare providers to develop and successfully implement EHR solutions (Joseph et al., 2014). However, research literature speaks of several problems associated with EHR implementations which have resulted in failed or partially successful implementations thereby revealing opportunities to identify factors and methods which would lead to successful implementations (Kruse et al., 2016; McGinn et al., 2011; Sidek & Martins, 2017; Zandieh et al., 2008).

Electronic Health Record Adoption Rates

A national EHR adoption survey conducted in the year 2015 involving 10,302 office-based physicians was conducted by the centers for disease control and prevention (CDC) (Jamoom & Yang, 2016). This survey results showed that that 53.9% of respondents had implemented a basic EHR system comprising of functions such as patient history and demographics, patient problem lists, physician clinical notes, list of patient medications and allergies, computerized orders for prescriptions, and ability to view laboratory and imaging results electronically. The study reported that 77.9% of respondents had implemented an EHR system that would meet MU criteria as defined by the Department of Health and Human Services. A study by Adler-Milstein and Jha (2017) found that EHR adoption by eligible healthcare providers grew from 3.2% in the years 2008-2010, to 14.2% in 2010-2015. Another study conducted in 2018 which was based on the healthcare information and management systems society (HIMSS) analytics' electronic medical record adoption model (EMRAM) dataset projected the maturation of EHR functionality adoption among United States hospitals through the year 2035 (Kharrazi et al., 2018). The authors argued that while MU has fueled the overall adoption of EHRs, hospitals are still lagging in implementing advanced features that enhance patient safety and care quality such as CPOE and opined that internal factors will become the main driver for EHR adoption in the future (Ford et al., 2008; Rahimi et al., 2009).

Factors Impacting Electronic Health Record Implementation Success

Successful HIT implementation is commonly evaluated using measures such as HIT adoption, technology acceptance, and clinical quality measures (CQMs) (Yen et al., 2017). From a MU standpoint, EHR adoption has been reported in terms of a percentage of healthcare organizations with specific EHR functionalities or capabilities. Such interpretation does not provide a holistic view of implementation success however, because it does not provide transparency and insights on the extent to which EHR functionalities have been implemented/used.

Technology Acceptance Factors based on the Individual Perspective

Several studies have approached EHR implementation success from an individual user's technology acceptance standpoint. Researchers have applied theories such as the technology acceptance model (TAM) and unified theory of user acceptance of technology (UTAUT) when measuring EHR acceptance by various stakeholders (Carayon et al., 2011; Gagnon et al., 2014; Kowitlawakul et al., 2015; Morton & Wiedenbeck, 2009; Mullings & Ngwenyama, 2018; Tavares et al., 2018; Tavares & Oliveira, 2016; Tubaishat, 2018; Vitari & Ologeanu-Taddei, 2018; Wilkins 2009). However, research literature cites the relatively lower predictive power of the TAM model in healthcare applications and recommends that TAM be integrated with other adoption theories (especially theories that include both human and social change process variables) when used in the healthcare context (Gangwar et al., 2014; Ward, 2013). HIT implementations are reported to have little impact on CQMs like patient mortality, adverse drug events and readmission rates (Agha, 2014). Yen et al. (2017) state that CQMs do not take into account the organizational and human factor perspective in objectively measuring implementation success. Based on the above results, a broad framework is needed to understand and predict EHR implementation success is required.

Need for a Broad Framework to Evaluate EHR Implementation Success

An emerging body of HIT research sees the need for incorporating socio-technical aspects in evaluating HIT implementations (Ash et al., 2012; Cresswell & Sheikh, 2014; Cresswell et al., 2012; Hameed et al., 2012; Hsiao et al., 2011). Cressewell et al. (2012) argued that disruptive technological innovations in healthcare offered a unique opportunity to understand and evaluate the changing inter-relationships between technology and human/organizational factors. Cressewell et al. (2012) emphasized that the nature of healthcare necessitated the study of processes associated with introduction of a new technology in social and organizational settings, due to the increasing number of technological functionalities that are incorporated across varied implementation contexts.

Westbrook et al. (2007) characterized the delivery of safe and sustainable HIT systems for the future as a *wicked problem* due to its ill-defined and ambiguous nature associated with strong moral, political and professional issues. Westbrook et al. (2007) theorized that the dynamic and multiple sets of complex interacting issues that evolve in an emergent social context, require that studies focus on the broader organizational and environmental contexts and processes.

Alternate theories such as the Sociotechnical Organizational Design theory, Social Shaping of Technology, HOT-fit and Normalization Process Theory seek to incorporate organizational, human (socio) and environmental factors (such as competitors). Such theories are increasingly being adopted to understand factors impacting HIT and EHR implementation success (Cresswell & Sheikh, 2014; Westbrook et al, 2007).

Based on the above research results, this study proposes to incorporate multidimensional factors to investigate EHR implementation success.

Organizational Learning Capability

Many definitions of organizational learning capability (OLC) have been put forth in research literature. Goh and Richards (1997) defined OLC as the managerial and organizational characteristic or element that facilitated the organizational learning process or encouraged an organization to learn. The influence of OLC on successful technological innovation implementation has been studied in several contexts. Aiman-Smith and Green (2002) examined the impact of organizational learning on the implementation of new manufacturing technology. Mat and Razak (2011) proposed a conceptual framework for exploring the relationship between OLC, knowledge complexity and their impact on technology implementation success. The impact of OLC on the successful implementation of technology innovations has been the subject of past research with reference to, for example, technology implementations involving Enterprise Resource Planning, e-business and Manufacturing sectors (Khamis et al., 2014; Robey et al., 2002; Uğurlu & Kurt, 2016). However, there are very few empirical studies in research literature that have incorporated OLC in studying successful HIT implementations such as EHR implementations, and no studies that have incorporated OLC with the unique set of factors considered in this study. Thus, this study fills a research gap in this regard.

Dynamic Capability and Absorptive Capacity

Dynamic capability (DC) is the ability of organizations to integrate, build and reconfigure their internal and external competencies to address rapidly changing business environments (Teece et al., 1997). DC has its roots in the knowledge-based view (KBV) theory that postulates that the foundation of a firm's performance lies in its ability to generate, combine, recombine or exploit knowledge (Grant, 1996). Knowledge, when understood as a strategic resource, is essential to a firm's ability to innovate and compete (Wang, 2013). Several researchers have focused on the notion of absorptive capacity (ACAP) as a unique DC which allows organizations to recognize the value of new, external information, assimilate it and apply it for organizational and competitive success (Cohen & Levinthal, 1990; Xie et al., 2018).

In recent years, information systems (IS) researchers have adopted the DC perspective to investigate how information technology (IT) can help organizations to overcome environmental challenges and respond to dynamic environments (Banker et al., 2006; Jarvenpaa & Leidner, 1998; Pavlou & El Sawy, 2006; Sambamurthy et al., 2003; Wheeler, 2002). Only a relatively small number of research studies have explored IT-enabled DC in healthcare (Davison & Hyland, 2002; Pablo et al., 2007; Reeves & Ford, 2004; Ridder et al., 2007; Singh et al., 2011). Likewise, only a relatively small number of research studies have investigated the impact of ACAP on healthcare technology innovation (do Carmo Caccia-Bava et al., 2006; Kash et al., 2014; Peng et al., 2014). This study contributes to existing research literature by considering the impact of ACAP on HIT implementation.

Service-Dominant Orientation

The dramatic rise in healthcare expenditures in the United States has led to calls for more value for the healthcare dollar. Healthcare service is an intangible product and cannot physically be touched, felt, viewed, counted or measured like manufactured goods (Mohamad Mosadeghrad, 2013). Healthcare organizations are considered service providers (Djellal & Gallouj, 2007). A paradigm shift is currently occurring with respect to how service and value are created, delivered and measured in healthcare, thereby building on the notion of service-dominant (SD) logic (Joiner & Lusch, 2016). Vargo and Lusch (2004) put forth the notion of service-centered dominant logic as an evolution of the marketing domain from a goods-dominant view. Karpen et al. (2012) extended the SD logic context to define SD orientation to apply SD logic in practice at an organizational level. Karpen et al. (2012) defined SD orientation as “A co-creation capability, resulting from a firm’s individuated, relational, ethical, empowered, developmental, and concerted interaction capabilities” (p. 21).

In recent years, healthcare scholars have adopted the SD framework in their efforts to evolve healthcare from a *goods* and *product* dominant perspective to one that provides holistic value through co-creation across multiple healthcare delivery contexts (Chakraborty & Dobrzykowski, 2014; Joiner & Lusch, 2016; McColl-Kennedy et al., 2012; Marufu & van der Merwe, 2019; Nyende, 2018; Turchetti & Geisler, 2013; Villapol et al., 2018; Yan & Chung, 2016; Zhang et al., 2015). However, most research has been conceptual in nature with a limited number of mixed-methods analysis. Based on the extant literature review conducted research studies have not considered the relationship between SD orientation and impact (i.e. positive association) on HIT/ EHR implementation success as has been done in this study. This study will attempt to empirically validate the association between the two, thereby adding to existing research literature.

Statement of the Problem

Based on the preceding discussion, it should be evident that understanding factors that impact EHR implementation success requires a multi-dimensional approach which incorporates technological, organizational learning and service perspectives. An emerging body of HIT research has identified the significance of incorporating socio-technical factors at the organizational level in investigating HIT implementation success. Scholars have studied the impact of OLC, ACAP and SD orientation on the technology implementation process and success in other domains such as organizational competitive advantage, marketing and supply chain management. However, there are no studies in the extant research literature reviewed that have considered the unique combination of individual technology acceptance factors and OLC, ACAP and SD factors to empirically measure EHR implementation success in the manner done in this study. This study therefore makes a needed contribution to research literature.

Purpose of the Study

The purpose of this study is to identify the impact of a unique set of technological attributes, organizational learning attributes, and SD attributes on EHR implementation success. It is the researcher's goal to create and empirically validate a framework for successful EHR implementation using these attributes. This study is guided by the following research questions:

1. Could EHR implementation success be predicted by a select combination of technology, organizational learning and service attributes?
2. Do ease of use, result demonstrability and performance expectancy impact EHR implementation success?
3. Does organizational learning capability impact EHR implementation success?
4. Does organizational absorptive capacity impact EHR implementation success?
5. Does a service-dominant orientation impact EHR implementation success?

Research Model

The research model proposed for the study is presented below in Figure 1.

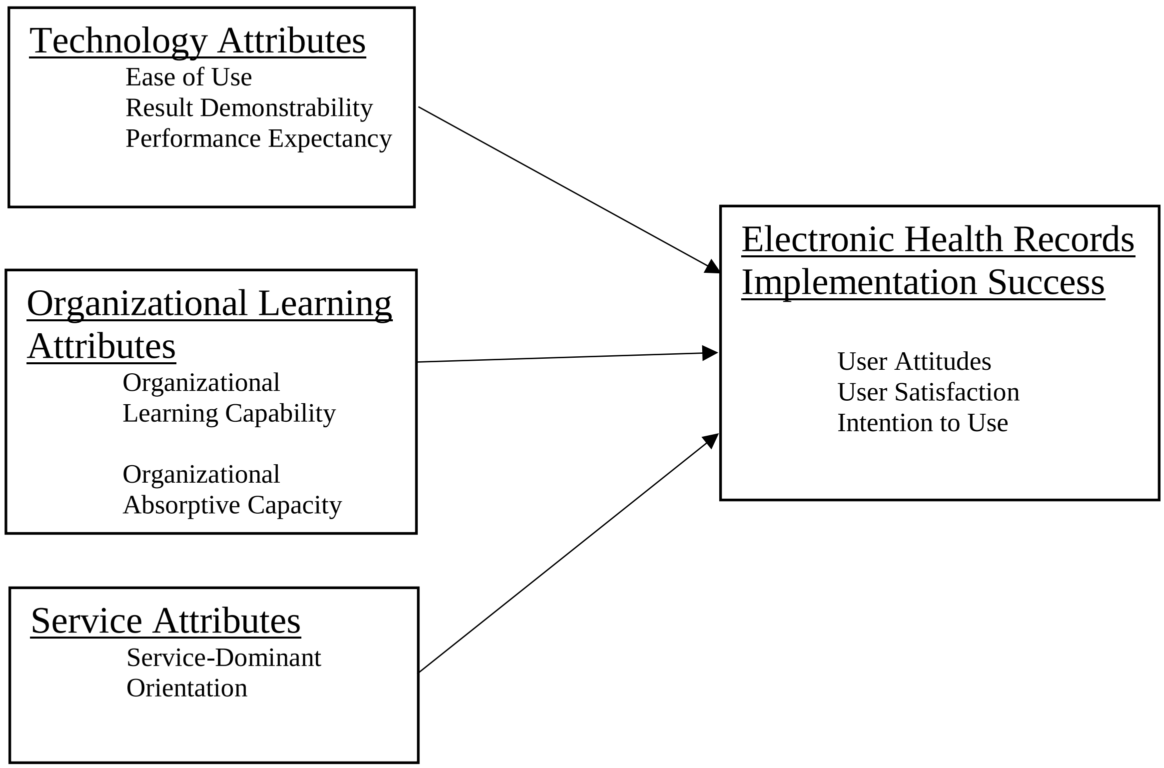

Figure 1. Research Model.

Significance of the Study

Successful EHR implementations provide numerous benefits to healthcare providers and researchers. Some of such benefits carry measurable revenue and productivity implications while others are relatively less quantifiable, but never-the-less equally significant to the healthcare service delivery ecosystem.

Information Technology Implementation Failures

Failed IT implementations impose a significant financial burden and prevent the intended benefits of the implementation from being realized (Lewis, B., 2003). Research shows that across sectors, at least 40% of IT projects either fail or are abandoned while fewer than 40% of large technology systems purchased from vendors meet their goals (Kaplan & Harris-Salamone, 2009). Some sources report up to 70% failure rates (Lewis, B., 2003). According to a report by the Standish Group (2015), 71% of technology projects either failed or were challenged (“The chaos report”, 2015). Specific to HIT implementations, systems need to have well-defined standards for interoperability and terminologies and comply with legal requirements (Kaplan & Harris-Salamone, 2009). While these are technical in nature, a growing body of research cites that problems with HIT implementations are sociological, cultural and financial in nature. These factors highlight the critical need to identify key factors that positively impact EHR implementations. This research study aims to identify a specific set of antecedents across the stated dimensions of individual technology acceptance factors and OLC, ACAP and SD factors with a view to helping EHR implementations succeed, thus reducing or eliminating the costs associated with failed implementations.

Benefits to the United States Healthcare Industry

The national healthcare expenditure in the United States is projected to grow one percentage point faster than Gross Domestic Product (GDP) each year between 2017 and 2026. As a result, the healthcare share of GDP is expected to rise from 17.9% in 2016 to 19.7% by 2026 (Cuckler et al., 2018). The United States ranks highest in healthcare spending among developed nations of the world ("U.S. Health Care Spending Highest Among Developed Countries", 2019). According to data released by the Organization for Economic Co-operations and Development (OECD), the health spending in the United States was estimated in 2018 at $10,586 per capita (“Health expenditure per capita”, 2019). Between 1999 and 2017, statistics show there has been a $10,000 increase in family insurance policy costs (Claxton et al., 2017). Cutler (2018) states that high medical spending in the United States is associated with substantial waste, leading to an unequal society. There is therefore an urgent need to optimize healthcare costs while eliminating wastes such as unnecessary spending. Failed HIT implementation costs contribute to such waste. By identifying factors which could lead to successful HIT implementation, healthcare organizations can incorporate them as improvement opportunities for healthcare delivery. This study aims to find and disseminate information leading to successful EHR implementations, which should be of great interest and benefit to the United States healthcare industry for aforementioned reasons and to help EHR implementations succeed.

Potential Benefits for Healthcare Providers and Patients

From the healthcare provider's perspective, effective implementation of EHRs has numerous advantages. Increased revenues by accurate and timely capture of patient charges, efficiencies gained by storing patient records electronically, reduced billing errors, reduction or elimination of unnecessary expenditure through better tracking, and improved legal and regulatory compliance are some benefits cited in research literature (Menachemi & Collum, 2011; Schmitt & Wofford, 2002; Williams 1990). Several studies have cited the increased re-use of test results and reduction in the need to mail hard copies amongst providers as advantages (Chen et al., 2003; Tierney et al., 1993; Wang et al., 2003). Other research studies have highlighted fewer tangible benefits such as improved operational performance and physician job satisfaction (Bhattacherjee et al., 2006; Menachemi & Collum, 2011; Menachemi et al., 2009).

From the patient perspective, improved quality of care, improved patient-physician communication and patient safety have often cited as benefits in research literature (Baker, 2001; Menachemi & Collum, 2011). With advances in smart phone technology and related mHealth initiatives, more patient-generated health data (PGHD) is now being collected (Genes et al., 2018). Integrating PGHD with EHR data provides both patients and healthcare providers a holistic view of patient health, which was historically not feasible. The findings of this study should help with successfully implementing EHR, which in-turn would lead to the realization of the aforementioned benefits.

Contributions to Academic Research and Industry

Electronically storing health information opens newer avenues for research that was previously not practical or feasible. Electronic health information enables public health research at a broader societal level to monitor macro-conditions such as, for example, disease outbreaks and surveillance against potential biological threats (Menachemi & Collum, 2011). Use of secondary data for research has been gaining momentum in the recent past, thanks to the application of modern data analytics techniques such as data mining. This in-turn has led to a reduction in the overall costs of doing research (due to primary data collection becoming unnecessary in many research situations), increased patient-centered research, and accelerated the rate of new medical discoveries (Weiskopf & Weng, 2013). This study aims to collect data pertaining to multi-dimensional success factors associated with EHR implementations. In addition, this study aims to uncover a set of technology attributes, organizational learning attributes, and service attributes associated with EHR implementation success. Conceivably then, academic researchers should find the results of this study useful and informative and also lead them to develop follow-up studies. In this manner, this study will be of benefit and interest to the academic community.

Practitioners, especially healthcare providers such as hospitals and clinics, are interested in successfully implementing EHR due to the laws in effect in the United States (and elsewhere around the world) as well as due to the benefits accrued from EHR implementation as explained earlier. Undoubtedly then, practitioners (especially healthcare providers such as hospitals and clinics) will also derive benefit from this study as it will help them with successfully implementing EHR in their own organizations and gaining the benefits from the implementation. In summary, it is expected that this study will contribute and be useful to the academic community and the practitioner community.

Improved Satisfaction among Physicians and Healthcare Professionals

According to research literature, there is a positive association between HIT usage and physician/healthcare professional career satisfaction leading to a higher quality of medical care (Elder et al., 2010). Menachemi, Powers, and Brooks (2009) examined the relationship between HIT adoption and overall physician practice satisfaction by surveying 14,921 physicians across the state of Florida in the United States. Their empirical findings suggested that users of HIT systems such as EHRs were generally happy (i.e. happy overall) with the performance of the technology. In addition, EHR use was independently associated with approximately 500% increase in their likelihood of satisfaction with HIT. Menachemi et al. (2009) also found that physicians who were satisfied with the level of computerization in their practices were also more likely to be satisfied with their overall medical practice. Based on these findings, Menachemi et al. (2009) concluded that physician’s EHR utilization may be indirectly related to desirable clinical outcomes by being associated with overall physician satisfaction. In a similar study, Davis et al. (2009) sought to examine the relationship between physician’s HIT use and quality of care across seven countries. Davis at al. (2009) found that physicians with higher use of HIT systems were significantly more likely to report being well-prepared to care for patients with multiple chronic diseases and with mental health conditions. The other conclusion made was that the ability of physicians to provide quality medical care to their patients and their satisfaction with the experience of practicing medicine was positively related to higher HIT use. A 2014

Rand research study on factors affecting physician professional satisfaction found that physicians approved of EHRs in concept due to its ability to remotely access patient information and improvements in quality of care (Friedberg et al., 2014). These examples underscore what physician's desire for enhanced satisfaction from their use of HIT systems such as EHRs. Findings from this research study can help add to the corresponding body of literature.

Summary of the Significance of this Study

The above discussion underlines the significance and importance of this study. The literature review conducted suggests that there is an inadequacy of empirical knowledge on the collective impact of technology factors, organizational learning factors and service-dominant orientation on EHR implementation. For all the reasons stated above, this study will make a significant contribution to extant research literature.

Definition of Terms

Absorptive Capacity: A unique dynamic capability which allows organizations to recognize the value of new, external information, assimilate it and apply it for organizational and competitive success. (Cohen & Levinthal, 1990, p. 128)

Adoption: The process through which an individual or other decision-making unit passes from first knowledge of an innovation, to forming an attitude toward the innovation, to a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision. (Rogers, 2003, p. 20)

Dynamic Capability: The ability of organizations to integrate, build and reconfigure their internal and external competencies to address rapidly changing business environments. (Teese, Pisano & Shuen, 1997, p. 516)

Electronic Health Record: An electronic record of health-related information on an individual that conforms to nationally recognized interoperability standards and that can be created, management and consulted by authorized clinicians and staff across more than one health care organization. ("The National Alliance for Health Information Technology report to the Office of the National Coordinator for Health Information Technology on Defining Key Health Information Technology Terms", 2008, p. 15)

Health Information Technology: The application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of health care information, data, and knowledge for communication and decision making. (Thompson & Brailer, 2004, p. 38)

Innovation: An idea, practice, or project that is perceived as new by an individual or other unit of adoption. (Rogers, 2003, p. 12)

Organizational Learning Capability: The managerial and organizational characteristic or element that facilitates the organizational learning process or encourages an organization to learn. (Goh & Richards, 1997, p. 577)

Service: The application of specialized competencies (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself. (Vargo & Lusch, 2004, p. 2)

Service-Dominant Orientation: A co-creation capability, resulting from a firm's individuated, relational, ethical, empowered, developmental, and concerted interaction capabilities. (Karpen et al., 2012, p. 21)

Summary

This chapter provided an introduction and context for the research study at hand by explaining the importance of EHR implementations to the future of healthcare delivery, presenting a preliminary literature review leading to the development of a research model for the study, and a detailed explanation of why this study is significant and what contributions it makes to extant research literature. In the next chapter, the development of the hypotheses for this research study will be presented accompanied by a thorough and detailed literature review leading to the logical development of the hypotheses.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Introduction

This chapter presents a literature review pertinent to the context of the study leading to a theoretical framework and the development of various hypotheses. The chapter begins by presenting a review of research literature pertaining to the benefits and challenges associated with information technology (IT) implementations, followed by a review of literature pertaining to health information technology (HIT) innovations. An innovation diffusion perspective from published literature on electronic health record (EHR) implementation is presented next. This is followed by a summary of scholarly work on EHR benefits to providers, patients and society, as well as EHR implementation barriers. Building on this theoretical framework, hypotheses are developed by reviewing extant literature and corresponding theories pertaining to technology attributes, organizational learning attributes and service attributes. It then presents several hypotheses which will be tested through data collection and statistical analyses. The chapter concludes with a discussion about the dependent variables used in the study to measure EHR implementation success.

Information Systems and Information Technology Implementations

Information systems (IS) has been defined as a combination of computer hardware, communication technology and software designed to handle information related to one or more business processes (Flowers, 1996). Implementation of an information system typically involves design, delivery and use of the software system in an organization through the use of IT, manual procedures, models, knowledge bases and databases. IT applications improve operational efficiency and act as catalyst for organizational innovation (OI) to restructure business processes (Yeo, 2002).

IS studies are interdisciplinary, integrating technological disciplines with management and disciplines such as psychology and sociology (Yeo, 2002). Research has identified IS and IT investments at an organizational-level to have a substantial effect on productivity levels (Black & Lynch, 1996; Brynjolfsson & Hitt, 2000; Lichtenberg, 1995; Mukhopadhyay et al., 1997). Studies have also shown that increase in IT capital investment has led to a decline in average firm size and a reduction in vertical integration (Brynjolfsson et al., 1994; Hitt, 1999). Porter and Millar (1985) stressed the organizational strategic competitive advantage enabled by IT. Porter and Millar (1985) argued that IT has the capability to alter industry structure by creating the need and opportunity for change, by lowering operating costs, and by enhancing differentiation amongst competitors. Porter and Millar (1985) presented several examples illustrating how IT has helped spawn new businesses by fueling innovation, making newer business models viable, and creating derived demand for newer products. Davenport (1993) argued that though IT is the most powerful tool to enable business process innovation, IT is rarely effective without simultaneous human innovations. Davenport (1993) emphasized that every example of IT as an enabler of new processes, is invariably accompanied by a corresponding change in the organizational and human factors. Bharadwaj et al. (1999) presented examples/evidence from research literature for IT-enabled intangible benefits including superior product quality, improved customer service, creation of knowledge assets, and synergy and coordination across organizational divisions. Through the use of empirical research, they demonstrated the positive association between IT investments and the future performance potential of organizations.

Information Technology Implementations: Acceptance and Adoption Challenges

While documenting the numerous organizational benefits of IT implementation, research literature also documents the various challenges related to IT implementation, acceptance and adoption. IT implementation is costly and has a relatively low success rate (Legris et al., 2003). The Standish group publishes an annual *chaos report* containing a survey of global IT project successes and failures. In 1995, Standish reported that approximately 16% of the 8,380 project implementations have been successful. By way of comparison, Standish's 2015 report that studied IT implementations across 50,000 projects found that 29% of the implementations have been successful. Cooper and Zmud (1990) outlined a six-stage model for studying IT implementations. Based on this framework, subsequent research has found that each stage of an IT implementation could face different challenges which could result in failed implementations. Munkvold (1999) identified categories of IT implementation challenges for inter-organizational systems, ranging from a lack of strategic needs for IT support, lack of user involvement, affinity to current-state technologies and process, adoption cost barriers, immature organizational change processes, and varying degrees of individual acceptance. Objective performance evaluation of IT system implementations is a challenging task due to interdependent variables and outcomes which are often difficult to quantify (Gunasekaran et al., 2006).

User acceptance of technology has been found to be the pivotal factor in determining the implementation success or failure of an IS project (Davis, 1993). Lack of user acceptance has been a long known impediment to the success of new information systems (Gould et al., 1991; McCarroll, 1991).

Researchers studying IT implementations have identified user resistance and factors leading to resistance, as critical antecedents to implementation success (Keen, 1981; Markus, 1983). Laumer and Eckhardt (2012) conducted an expansive literature review on user resistance theories to help answer why individuals resist or reject technology. One body of research focuses on resistance behaviors such as passive resistance, active sabotage, and covert procrastination following perceived threats from initial interactions with technology (Lapointe & Rivard, 2005; Martinko et al., 1996). Past academic research has studied resistance in terms of interaction of the system being implemented and the context of its use. Factors such as intra-organizational distribution of power and organizational politics have been identified as sources of resistance (Markus, 1983). Researchers have applied social network theories and social influence as predictors of non-adoption behaviors pertaining to IT implementations (Eckhardt et al., 2009). Ali et al. (2016) in their work on categorizing user resistance to IT adoption identified major sources of resistance including distorted perception, low motivation for change, lack of creative response, political and cultural deadlock, and organizational factors such as leadership inaction and lack of the necessary organizational capabilities.

A substantial body of research on IT implementations has focused on organizational factors. For example, studies have shown that adoption of innovative technologies such as Blockchain, Enterprise Resource Planning (ERP) systems and Cloud Computing creates increased uncertainty and puts pressure on organizations (Holotiuk & Moormann, 2018; Ozkan et al., 2012; Plyviou et al., 2014).

Several scholars have highlighted the need for organizations to break away from established innovation paths in order to keep pace with evolving product and process innovations fueled by IT (Svahn et al., 2017; Tilson et al., 2010; Tiwana et al., 2010; Yoo et al., 2010). To embrace IT innovations organizations need to develop newer capabilities to identify novel ideas within existing organizational context (Henfridsson & Lindgren, 2010). This could be a challenging task as it often involves shifts in organizational identity and organizational culture (Lucas & Goh, 2009; Tripsas, 2009) leading to newer organizational hierarchies and constructs (Baldwin & Clark, 1997; Henfridsson & Lind, 2014). Drawing on empirical studies across several industries, Svahn et al. (2017) categorized organizational challenges when developing and adopting digital IT innovations comprising of innovation capability: *existing versus requisite*, innovation focus: *product versus process*, innovation collaboration: *internal versus external*, and innovation governance: *control versus flexibility*.

Organizational change management is another factor that impacts success of IT implementations (Dwivedi et al., 2015). This takes place invariably in a complex business and social environment (Bunker, 2013). Dwivedi et al. (2015) also emphasized that *conventional wisdom* for organizational IT implementation must include factors such as top management support, presence of a project champion and use-involvement, the lack of which has led to many IT implementation failures. Several researchers have emphasized the need for considering factors such as evolving organizational structure, people, processes, culture and politics to ensure truly successful outcomes with respect to IT implementations (Dwivedi et al., 2015; Markus et al., 2000; Orlikowski & Robey, 1991; Soh et al., 2000; Strong & Volkoff 2010; Volkoff, Strong, & Elmes, 2007).

Information Technology Implementations: Best Practices, Lessons Learned

Research literature informs us about best practices and lessons learned with respect to successful IS and IT implementations. Top management support continues to be identified as a critical antecedent (Elbanna, 2012; Markus, 1983). Availability and use of the services of a formal project champion has been cited as a best practice (Kirsch et al., 2002). Research literature stresses the importance of end-user buy-in and end-user involvement when implementing IT solutions (Barki & Hartwick, 1994). A lesson documented is the need to constantly re-think and re-engineer the broader business and organizational workflow processes in tandem with implementing IT solutions (Lee et al., 2008). Several scholars have proposed a systems approach to standardizing and implementing IS integrations (Lee & Myers, 2004).

Past research reveals that with new IT implementations come potentially newer organizational, cultural and political structures (Orlikowski & Robey, 1991; Markus et al. 2000; Soh et al. 2000). Lack of this recognition has been cited as a reason for failure in several IT implementation scenarios (Bussen & Myers, 1997; Dwivedi et al., 2015; Lee & Myers, 2004; Myers 1994). Several researchers have underscored the need to establish key performance indicator variables for evaluating implementation success within the project context (Bamberger, 2008; Johns, 2006).

Healthcare Information Technology: An Information Technology Innovation

With ever increasing healthcare costs and healthcare quality concerns in the United States and in other countries of the world, researchers and practitioners alike anticipate that HIT implementations will provide many benefits to healthcare organizations as described in this section. In addition, successful implementation of HIT should help to address the implementation, acceptance and adoption challenges discussed in the previous section.

Opportunities and challenges related to HIT implementations are discussed in the following paragraphs.

HIT has the potential to contribute significantly to public health improvement and healthcare provider performance through enhancement of efficiency and effectiveness resulting in cost savings, improvement in the quality of care, evidence-based medicine, and greater patient engagement in their own healthcare (Blumenthal, 2010). Clinical decision support systems (CDSS), telemedicine, mHealth and EHRs are examples of HIT innovations (Labrique et al., 2013; Serova & Guryeva, 2018). Knowledge systems known as CDSS use two or more items of patient data to generate case-specific advice (Van der Lei & Talmon, 1997). Most CDSS systems comprise of the knowledge base, the inference or reasoning engine and a mechanism to communicate with the user (Servoa & Guryeva, 2018). The CDSS systems typically use a form of artificial intelligence (AI) technique called machine learning to recognize patterns in clinical data. Telemedicine is considered to be a major HIT innovation at the technological, social, and cultural levels (Gagnon et al., 2003). Telemedicine utilizes IT to enable remote delivery of healthcare at distant locations which are difficult to reach and in rural areas. Telemedicine in an innovation that has generated a new model for patient interaction with other entities in the healthcare ecosystem such as hospitals, pharmacies, physicians, and government agencies (Burney et al., 2010). The invention of mobile communication devices coupled with social media has presented opportunities for disease prevention and management by extending health interventions beyond the reach of traditional care – an approach referred to as mobile-health or mHealth (“Welcome to mHealth Knowledge “, n.d.). HIT has made possible the treatment of chronic diseases such as diabetes and epilepsy in non-traditional clinical settings because patients can collect and share relevant data at any time through the use of mobile technologies, allowing for rapid convergence towards optimal treatment (Estrin & Sim, 2010).

One of the most significant health information technology implementation in recent times is the implementation of EHRs (Crane & Crane, 2006; Elberg, 2001; Krist, 2015). In the following section, EHR implementation is discussed from an innovation diffusion perspective.

Electronic Health Records Implementation: An Innovation Diffusion Perspective

Several academic researchers have approached the study of EHR implementation and use from an innovation diffusion perspective. Roger defined innovation as "an idea, practice or object that is perceived as new by an individual…" (Rogers, 1995, p.11). It is appropriate to note in this context that newness is not defined by the actual length of time since the innovation's discovery or initial use. In other words, it is not true that if an idea, practice or object "seems new to the individual, it is an innovation" (p. l 1). Instead, Roger's Innovation Diffusion Theory (IDT) identified five perceived attributes of innovation as *Relative Advantage, Compatibility, Complexity, Trialability and Observability*. *Relative advantage* is the degree to which an innovation is perceived as being better than the idea it supersedes. *Compatibility* is the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters. *Complexity* is the degree to which an innovation is perceived as relatively difficult to understand and use. *Trialability* is the degree to which an innovation may be experimented with on a limited basis. *Observability* is the degree to which the results of an innovation are visible to others.

Based on Roger's IDT, Lee (2000) studied the implementation of EHR system at Medical University of South Carolina as a technology innovation diffusion problem. Lee's study concluded amongst EHR users, the most positive perceptions were for the *Relative Advantage,* *Compatibility, Result Demonstrability*, and *Trialability* dimensions. Lee's findings suggested that Physician's acceptance of EHRs would require alternate training methods aligned with their usage patterns. Dansky et al. (1999) in their study on physician readiness to use EHRs found that the culture of an organization including its supportive elements influenced both successful implementation and continued use of EHR. Dansky et al. (1999) emphasized the need to identify and understand organizational practices that most strongly support or compromise work redesign efforts. Elberg (2001) viewed EHR as not just a technical innovation, but also a product and service innovation in healthcare. Elberg argued that viewing EHR as merely the automation of a paper-based system would amount to taking a very narrow view. Instead, organizations should approach it as a means for innovating the process (process innovation). This study hypothesized that the ideal outcome of such an innovation would be clinicians spending more time creating knowledge from clinical information and less time managing it, which in-turn would result in clinicians with high information competency who will be capable of further innovating products and services.

Crane and Crane (2006) viewed EHR as a technological innovation which, when utilized with other HIT innovations such as computerized patient order entry (CPOE), could help prevent medication errors in hospitals. Medication errors are a direct result of how health systems are organized and how healthcare is delivered (Crane & Crane, 2006). To holistically address this problem, Crane and Crane proposed a framework comprising a systems-approach driven by failure mode effects analysis (FMEA) and use of HIT innovations such as EHRs, to reduce medication errors and improve patient safety. Emani et al. (2012) studied patient acceptance of personal health records (PHRs), an Internet-based tool, to access components of EHRs. Emani et al. (2012) developed this as an innovation diffusion problem based on IDT. Their study found that the diffusion of innovation model provided an appropriate theoretical and empirical framework to identify factors that distinguish PHR users from non-users. The ease of use and relative advantage offered by the PHR emerged as critical factors pertaining to PHR use and prediction of value of the PHR.

In a similar study, Tansel (2013) highlighted complementary innovation avenues being realized through PHR-EHR integration. Neumeier (2013) hypothesized that EHR implementation success can be viewed as a three-phased approach of planning for change, implementing change, and cementing change. The study proposed a model based on Roger's IDT and Kotter's Change Management Theory (CMT) to successfully implement EHR as a technological innovation. Neumeier (2013) argued that successful EHR implementation is a change management challenge and hence using Roger's IDT in conjunction with Kotter's CMT together provided the necessary and appropriate structure for EHR adoption. Krist (2015) stressed the innovation aspects of EHRs that strengthen the physician-patient relationship leading to both healthier patients and happier doctors. In this context, Krist (2015) called for a concerted effort by HIT developers, healthcare providers and administrators to collaborate and innovate with a view to improving the effectiveness of healthcare delivery. The concept of open innovation refers to the need to look outside the traditional boundaries of the organization to innovate, make the boundaries of the organization more permeable, involves both internal and external knowledge, and is applicable to complex organizations such as healthcare providers (Chesbrough, 2003, Chesbrough et al., 2006; Gassmann et al., 2010; Huizingh, 2011; Piller & West, 2014; Wass & Vimarlund, 2016). Several of these studies focused on the use of EHRs as a means to involve more stakeholders in solving complex challenges to improve the quality of health information services. In a related study, Wass et al. (2017) presented patient's access to

EHRs as a service innovation. Service innovation is defined as “a new service or such a renewal of an existing service which is put into practice and which provides benefit to the organization that has developed it” (Toivonen & Tuominen, 2009, p. 893). Wass et al. (2017) argued that service innovation empowered patients to engage as a more active stakeholder in the healthcare ecosystem. Wass et al. (2017) viewed such innovation as being realized from the renewal of existing services during the interaction between patients and healthcare professionals. The following section presents and discusses some specific benefits resulting from electronic health records implementations.

Electronic Health Records Implementation: Benefits

EHRs have widespread use and applications, especially in the United States (Blumenthal & Tavenner, 2010). Research has identified benefits resulting from the use of EHRs including better-managed patient care, improved efficiencies resulting in lower health care costs, and improved clinical decision making (Bell & Thornton, 2011; Goetz et al., 2012; Menachemi & Collum, 2011; “What are the advantages of electronic health records?”, n.d.). Enhancement in the quality of patient care can be achieved through access to complete and up-to-date information pertaining to the patients at the point of care, quick access to the entire patient health information enabling a more coordinated and efficient care, efficient diagnosis and treatment accompanied by reduction or elimination of medical errors, and provision of relatively safer care (“What are the advantages of electronic health records?”, n.d.). In addition, EHRs may help to enhance the interaction and communication between the healthcare receivers and the healthcare providers, thus improving the quality and reliability of drug prescribing and promoting legible and complete documentation. Tertiary benefits include enhanced patient data privacy and security, secure sharing of electronic information with patients and other clinicians, improved provider productivity and work-life balance, effective population health management, and availability of de-identified clinical data for research purposes (Bell & Thornton, 2011; "What are the advantages of electronic health records?", n.d.; Goetz et al., 2012; Menachemi & Collum, 2011).

Benefits to Healthcare Receivers (Patients) from Using Electronic Health Records

Quality of care has been defined as "doing the right thing at the right time in the right way to the right person and having the best positive results" ("Healthcare Research", 2004, p. 12) and "avoiding injuries to patients from the care that is intended to help them" (Baker, 2001, p. 3) which speaks to patient safety when receiving healthcare. It is expected that using EHRs will positively impact both aspects as explained below.

Due to the availability of EHRs which can be accessed by the healthcare receivers (patients) and the healthcare providers (physicians), chronic disease management becomes simpler, faster and convenient (Bell & Thornton, 2011). For example, hypertensive patients can enter their blood pressure and other key indicators from the convenience of their home while their doctors and nurses can access such information remotely, perform health assessments based on such data, and adjust drug dosage and treatment plans in real time without waiting for the patients' next visit to the hospital.

Access to, and accuracy of patient documentation is essential in ensuring the ability of healthcare providers to reduce medication errors and enhance patient safety (Goetz et al., 2012). Due to the use of EHRs, patient data is no longer obscured and difficult to find because EHRs allow for the patient's past medical history to be presented in an organized and easily accessible manner at various points of care (Goetz et al., 2012). Menachemi and Collum (2011) presented several examples of the effective use of EHRs in conjunction with other HIT innovations such as

CDSS and CPOE, to reduce medication errors significantly (Bates et al., 1998; Bates et al., 1999a; Bates et al., 1999b; Devine et al., 2010).

EHRs enable easier and more effective communication between the healthcare providers and the healthcare receivers (Goetz et al., 2012; Zhang et al., 2012). King et al. (2011) conducted a study to assess whether self-reported EHR use by physicians provided clinical benefits. King et al. (2011) surveyed 5,232 physicians from a collective database of the 2011 national ambulatory medical care survey (NAMCS) and the 2011 NAMCS physician workflow survey. Among the respondents 78% of physicians reported that the use of EHRs enhanced patient care. A majority reported that EHRs helped them to access patient charts remotely, alerted them to a potential medication error, and alerted them to critical lab-test values. Another study found that computerized physician reminders increased the use of influenza and pneumococcal vaccinations from 0% to 35% and 50% respectively for hospitalized patients (Dexter et al., 2001). Willson et al. (1995) found a significant association between computerized reminders and pressure ulcer prevention in hospitalized patients. Willson et al. (1995) found a 5% decrease in the development of pressure ulcers six months after the implementation of computerized reminders that targeted hospital nurses.

Another area of optimization enabled by EHRs is a reduction in rate of redundant diagnostic testing. A study by Niès et al. (2010) found that point-of-care computerized reminders of previous blood tests significantly reduced the proportion of unnecessarily repeater tests. Other studies found an 18% decrease in tests ordered for medical visits in the emergency department (Wilson et al., 1982), a 27% decrease in redundant laboratory tests of antiepileptic medication levels in hospitalized patients (Chen et al., 2003), and a 24% reduction in redundant laboratory tests in a hospital (Bates et al., 1999).

Benefits to Healthcare Provider Organizations from Using Electronic Health Records

Research literature has documented several benefits from using EHRs for healthcare provider organizations. These include financial benefits, legal benefits, and, several intangible benefits such as physician satisfaction. Population health management is a broader advantage to both healthcare providers and society at large.

Financial and Legal Benefits

Presence of standardized data and complete documentation enables healthcare providers to automate clinical documentation and file claims in a timely manner, and minimizes lost revenue due to denial of claims (Bell & Thornton, 2011). Additional efficiencies are gained by integrating hospital and professional billing systems with EHRs to provide for automated charge capture and reduced time and resources needed for manual charge entry, leading to a more accurate billing and reduction in lost charges (Menachemi & Collum, 2011). Charge lag delays can be minimized by automatically triggering charges in an EHR system at the point when the healthcare provider closes the patient encounter. This also helps minimize insurance denials associated with late filing of charges (Bell & Thornton, 2011). Reductions to outstanding days in accounts receivable and lost or disallowable charges can potentially lead to improved cash flow (Agrawal, 2002). In addition, EHR reminders to providers and patients about routine health visits can increase patient visits thereby enhancing revenue (Mildon & Cohen, 2001). Other operational benefits from a financial standpoint include reduction of redundant use of tests, reduction in the need to mail hard copies of test results to different providers, reduced costs for patient chart pulls by making it readily available, reduced cost to maintain supplies for paper charts, reduced transcription costs through point-of-care documentation and other structured documentation procedures (Agrawal, 2002; Chen et al., 2003; Ewing & Cusick, 2004; Tierney et al., 1993; Wang et al., 2003). One study found a significant decrease in staff resources dedicated to anemia management for hemodialysis patients when a CDSS was used for medication dosing (Miskulin et al., 2009). EHRs have facilitated the ability for an *open access* appointment scheduling policy enabling most patients requesting appointments to be seen the same day or within 24 hours (Zaroukian & Sierra, 2006), thereby improving revenue for healthcare providers.

From a legal standpoint, EHRs facilitate improved legal and regulatory compliance through increased data security and patient confidentiality supported by controlled and auditable provider access (Agrawal, 2002). One study found that physicians using an EHR had relatively fewer malpractice claim payouts (Virapongse et al., 2008). Virapongse et al. (2008) reported that while 6.1% of physicians with an EHR had a history of malpractice claim payouts, 10.8% of physicians without EHRs had a history of malpractice claim payouts. Menachemi and Collum (2011) hypothesized that the reduction in malpractice claim payouts for physicians using EHRs could be the result of increased and better communication among caregivers, increased legibility and completeness of patient records, and increased adherence to clinical guidelines, all enabled by EHRs. Physicians reported efficiencies in performing activities such as accessing patient information, renewing prescriptions in a timely manner, responding to reminders and alerts for tests and preventive care interventions, and accessing laboratory results in real-time. Two aspects related to improved physician satisfaction were the reduction in pager-related interruptions when physicians were not at the clinic, and improved information support for decision-making when they were on-call. Increased staff satisfaction also resulted through peer learning whereby staff could learn from each other by reading the records entered by their colleagues (Zhang et al., 2012).

Intangible Benefits

Menachemi et al. (2008) in their study found that Florida hospitals with greater investments in EHR technologies had more desirable rates on a variety of commonly used quality indicators. In another study, Menachemi et al. (2008) found that computerized records and order entry were associated with lower mortality rates, and the use of CDSS was associated with fewer complications. Based on their findings, Menachemi et al. (2008) concluded that provider’s adoption of HIT systems was associated with desirable quality outcomes across the hospitals in their study. Other less tangible benefits have been associated with EHR use. In a study conducted by Bhattacherjee et al. (2006), Florida hospitals with a greater adoption of HIT (such as EHR) had higher operational performance as measured by the outcomes of Joint Commission on Accreditation of Healthcare Organizations (JCAHO) site visits. Clinical HIT adoption demonstrated the strongest effect on operational performance because technologies such as EHR, were found to directly improve and transform the management and delivery of healthcare. In a similar study, Thakkar & Davis (2006) conducted a national survey of hospitals in the United States to identify the status of EHR systems in hospitals. Small-sized hospitals that had deployed EHR systems reported a significant improvement in their work efficiency and time management. In addition, ease of interoperability and quality of care were identified among the top 10 benefits of utilizing EHRs.

Zaroukian and Sierra (2006) reported on the EHR implementation program at the Internal Medicine Clinic of the Michigan State University. This clinic provided approximately 15,500 office visits, more than 20,000 telephone encounters and 4,000 outgoing referrals annually. A phased implementation model was used to incrementally implement EHR. Benefits reported by nurses and medical assistants included improved speed of access of patient chart information, improved ability to process patient requests for assistance without multiple telephone calls and voice-mail messages, and the ability to handle patient care issues through the use of automated workflow process. Nurses and medical assistants reported their appreciation of the availability of documentation templates, text macros, and clinical decision support such as anticoagulation management which facilitated the faster creation of patient documentation and created the ability to automate internal and external referrals. Research has identified yet another intangible but arguably the most notable association – that between EHR use and physician satisfaction, as well as their career satisfaction (Elder et al., 2010; Menachemi et al., 2009). Improved physician satisfaction can lead to better quality of care, better drug prescribing behaviors, and increased retention in medical practices (Linzer et al., 2000; Pathman et al., 1996).

Population Health Management

The use of EHRs enables physicians to periodically extrapolate reports for specific patient populations and utilize them to track patient care and quality-improvement discussions during clinical encounters (Goetz et al., 2012). Computerized physician reminders for timely patient vaccination and immunization administration helps lower the risk of disease outbreaks in communities (Menachemi & Collum, 2011). Making patient data electronically available improves the ability to conduct research due to increased opportunities for quantitative analyses which helps to identify evidence-based best practices (Galewitz, 2011). As EHR adoption grows, it provides public health researchers to use electronic clinical data aggregated across populations to conduct research that is of benefit to the larger society (Menachemi & Collum, 2011). By combining this data with other complementary sources such as over-the-counter medication purchases and school absenteeism rates, they would be able to better monitor disease outbreaks and surveil for potential biological threats (Kukafka et al., 2007).

Electronic Health Records: Implementation Barriers

EHR implementation barriers identified in academic research literature include financial issues, workflow changes, temporary loss of productivity associated with EHR adoption, lack of training, privacy and security concerns, and unintended consequences. A detailed discussion is presented below.

Productivity and Usability Challenges

One of the widely acknowledged obstacles to EHR implementation is the loss of physician and nurse productivity during the initial stages of adoption. Hill et al. (2013) conducted a time study at the emergency department of St. Luke's Health Network, Pennsylvania in 2012 to evaluate physician's productivity using EHRs. Hill et al. measured physician time usage categorized as direct patient contact, EHR data entry, consultation and discussion with colleagues, and review of test results. A total of 16 physicians were tracked 30 hours. Results showed that the mean percentage time spent in the data entry category was 44%, in the patient contact category was 28%, in the discussions with colleagues category was 13%, in the reviewing test results and records category was 12%, and 3% of time was spent on other activities. Computer mouse clicks for each physician (on a per-patient and per-hour basis) were recorded and averaged over cases of varying complexities. An extrapolation involving a typical 10-hour shift resulted in 4,000 clicks. Other time-and-motion studies in clinical practice have shown that an additional 3 hours per week of physician time is lost on data entry tasks which reduces to the same extent the time effectively spent on patient-centered care activities (Sinsky & Beasley, 2013).

The above research study seems to highlight that EHR systems need to be better designed from a usability perspective. Unlike in certain industries such as aviation and automobile where usability aspects are built into the product, in the healthcare industry, the incorporation of usability principles into EHRs has been inconsistent and sporadic (Zhang & Walji, 2011). Prior academic research has demonstrated that the incorporation of usability principles in EHR design is critical to its implementation success (Ash et al., 2004) Despite this, an American Medical Association sponsored research and development (RAND) study (2013) of physician practices from six states, revealed physician dissatisfaction (both personal and professional) with EHRs due to inadequacy of usability features in EHRs (Friedberg et al., 2013).

Unintended Workflow Consequences

While EHRs encourage physicians to become more *hands-on* in interacting with patient records, they have created an unintended adverse effect of *electronic siloing* (Stoller, 2013). In a pre-EHR era, an outpatient clinic would have examination rooms lined up with a long desk where clinicians would review films, gather thoughts and discuss recommendations. This has been replaced in the EHR era by workstations spread out along the corridors to enable physicians to enter notes electronically thus reducing face-to-face interactions among physicians (Stoller, 2013). A more detrimental variant is when there are fewer computers available at a given point in time. This prompts physicians to search for an available location elsewhere, thus separating them even more from nurses or other physicians located near-by that are caring for their patients, thereby causing more isolation (Stoller, 2013).

There are more subtle unintended consequences beyond electronic silos. Conflicts between electronic and paper-based systems arise when physicians whose personal preference is to use paper records as formal documentation create two distinct sources of medical records. Busy physicians might enter data in the wrong section of the EHR causing confusion to anyone accessing it downstream, and often leading to duplication. Longer-term use of EHR increases physicians' over-dependence on the technology to the point where they may have trouble remembering standard doses and formulary recommendations which they previously may have committed to memory (Jones et al., 2011). As well, EHR's continued use increases demand for newer custom-features and functionality necessitating more resources devoted to EHR implementations in an on-going manner. With the IT department now at the center of a healthcare provider's functioning, it might create newer organizational power structures that were previously non-existent (Jones et al., 2011).

Patient-Physician interaction workflows are also negatively impacted if physicians are not cognizant of their actions. In a comprehensive report on incorporating HIT into workflow redesign, Carayon et al. (2010) stated that several communication patterns are reported in research literature ranging from the provider *mostly* looking at the screen and using computer-guided questioning to enter information, to the provider alternating attention between the patient and the screen. Carayon et al. (2010) found that patients too reported similar concerns about the effects of computer use on their interactions with.

Training

Training plays a fundamental role in delivering HIT implementations. Studies have reported a range of factors from insufficient training to poorly scheduled training sessions with irrelevant training material as impediments to EHR implementations (Kruse et al., 2016; McGinn et al., 2011; Sidek & Martins, 2017). Other studies have highlighted cognitive barriers in using EHRs due to a lack of appropriate IT training (Bloom et al., 2000; Johnson, 2001; Snyder-Halpern & Wagner, 2000).

Bloom et al. (2000) conducted a study to identify benefits and barriers among users of the Behavioral Risk Factor Surveillance System (BRFSS), the world's largest ongoing health surveillance system. Data gathered from multiple focus groups of users highlighted the lack of analytical ability as a barrier to adopt the BRFSS. Users cited the lack of skills and lack of confidence to interpret BRFSS data, as an impediment to holistically take advantage of the value it delivered. The availability of additional training was identified as a significant contributor to improved use. Johnson (2001) conducted an expansive literature review to elucidate barriers to HIT adoption among pediatric healthcare professionals (PHCPs). One of the key themes that emerged from this study, was the physician's cognitive barrier due to insufficient skills or ability to use HIT. Many PHCPs had to learn to use HIT systems without the benefit of formal study. PHCPs identified a lack of IT training as a major barrier to using technologies they considered valuable. To overcome these barriers, Johnson (2001) proposed convening hands-on seminars and workshops for PHCPs, as well as developing IT adoption models that paired experts with less technically experienced PHCPs. In a case study of implementing a vendor based HIT system at a non-profit tertiary care hospital, Snyder-Halpern and Wagner (2000) highlighted the impact of insufficient representation among stakeholder groups on training and subsequent rollout. Lack of awareness and training on the IT development life cycle became a major challenge to overcome. When it came time to adopt the HIT system, clinicians became stressed in dynamic and demanding clinical situations. Based on the lessons learned from this implementation, Snyder-Halpern and Wagner (2000) summarized risk mitigation recommendations to overcome such barriers to HIT implementations.

Cost of Implementation and Organizational Change Management Barriers

Several researchers have cited upfront investment costs, slow and uncertain financial payoffs, and the need for healthcare providers to absorb a portion or all of the set-up costs as potential barriers to EHR implementation (Hillestad et al., 2005). Hillestad et al. (2005)

projected the cumulative cost for 90% of hospitals in the United States to adopt EHRs to be $98 billion and for 90% of physicians (to adopt EHRs) to be $17.2 billion. Miller and Sim (2004) reported high initial physician time costs per patient for a certain period after EHR implementation. Physicians spent more time per patient when EHR was used (in comparison to when EHR was not used) due to difficulties with using the technology, complementary changes and lack of adequate support, and lack of electronic data exchange between EHR and other HIT systems.

Organizational change management, or lack thereof has been reported as an implementation barrier. Sassen (2009) surveyed nurse's perceptions about EHRs and their reasons for accepting or rejecting it. Nurses emphasized the need for an inclusive change management process wherein they are part of the shared decision-making across all phases of EHR implementation. Mason et al. (2017) conducted a phenomenology study to explore rural primary care physicians and physician assistant's experience regarding EHR implementation barriers. Lack of change management practices at rural medical facilities was identified as one of the four main themes pertaining to implementation barriers. Lack of top-down management support and ownership in implementing EHR systems was cited by several participants in the study.

Privacy and Confidentiality Barriers

Several studies have reported privacy concerns resulting from EHR use. Physicians doubt if EHRs are secure enough to store patient information, and fear that EHR use may cause patient data to be accessible to those not authorized to view it, which in-turn could lead to legal problems for the healthcare provider organizations and the healthcare providers as well as physicians (Boonstra & Broekhuis, 2010). In recent years, several incidents of accidental loss or theft of sensitive patient data have been reported. A survey by Ponemon Institute, a privacy and data protection research firm found that 90% of health care providers have had at least one data breach over the last two years at the time of publication of the article (Abelson & Creswell, 2015). In February 2015, Anthem, one of the country's largest insurance providers reported that hackers had succeeded in gaining access to its systems exposing information about 80 Million patients (Abelson & Creswell, 2015). A southern Illinois hospital received a *ransom* e-mail with confidential patient health record information that hackers obtained from the hospital's network, threatening to release it unless they received a substantial payment from the hospital (McCann, 2014). In another instance, two hospital employees were terminated after having been found to have illegally accessed an Ebola patient's records at the Nebraska Medical Center in Omaha, Nebraska (Butler, 2014). While paper-based records are not fully protected against unauthorized access, it follows from the foregoing discussion that newer forms of threat involving unauthorized access to patient records arise with EHR implementation and use. This implies that that healthcare provider organizations and the healthcare providers (physicians) have to prepare to deal with such newer forms of threat involving unauthorized access to patient records.

Electronic Health Record Vendor Maturity and Dealing with Meaningful Use Guidelines

As of April 2014, only eight eligible hospitals had formally attested to Stage 2 of the meaningful use (MU) guidelines pertaining to EHR implementation and use, while 3,877 had attested to Stage 1 (Goedert, 2014). The main reason for the low Stage 2 attestation was that several EHR vendors struggled to successfully provide the core functionality which was necessary to be compliant with Stage 2 meaningful use stipulations. It has been reported that less mature vendors have been playing catch-up by *checking off boxes* without actually paying attention to real-world clinical workflows. This has posed additional challenges for larger healthcare provider networks that employ a mix of EHRs and related IT systems. According to Kauth, Interim CIO of CentraState Healthcare System in New Jersey, every vendor implemented core functionality differently without giving thought to how their other systems had to be modified (Goedert, 2014). Goedert (2014) reported that as a result, there has been the need for extensive re-work leading to frustration for everyone involved. In addition, some EHR vendors have exploited the situation to up-sell costly additional applications to their customers (healthcare providers) thereby increasing their financial burden and at the same time increasing their EHR implementation costs. Even major EHR vendors in the United States such as Epic Systems headquartered in Madison, Wisconsin have had their share of challenges. The Chief Medical Information Officer of the University of Mississippi Medical Center stated the lack of appropriate analytics functionalities in Epic EHR as a roadblock to their successful meeting of MU requirements (Goedert, 2014).

There were over 400 EHR vendors in the marketplace as of 2006 (“Selecting the Right EMR Vendor”, 2006). From the foregoing discussion it can be concluded that many EHR vendors are not yet fully equipped to respond to the dynamic healthcare landscape. Therefore EHR vendor selection can have a significant impact on the success or failure of EHR implementations.

Interoperability Challenges

Interoperability of EHR systems with other applications has been cited as an implementation barrier in academic and practitioner literature (Bates, 2005). Lack of standardization in EHR systems development results in different EHR vendors developing systems which may or may not have comprehensive functionalities. This creates a situation whereby a physician needing access to supplementary records such as laboratory and radiology results is required to log in to other applications besides the EHR platform to obtain this information, and may have to re-enter this information into the EHR themselves for subsequent use, leading to inconvenience and consumption of additional time (Bates, 2005).

While academic research literature discusses various benefits to patients, physicians, healthcare organizations and society resulting from implementation of EHRs, it also discusses barriers to successful implementation at both individual and organizational levels. In recent times, there has been discussion in research literature about the service innovation aspect and its application to EHR implementations (Chesbrough, 2003; Chesbrough et al., 2006; Piller & West, 2014; Wass & Vimarlund, 2016; Wass et al., 2017).

Hypotheses Development

As discussed earlier in this chapter, EHR is considered a HIT innovation and its successful implementation is critical to bringing many benefits to the healthcare providers, to the healthcare receivers and to society at large. Uncovering factors that have a positive association with EHR implementation success will help healthcare organizations to successfully implement EHR and making available its benefits.

Consistent with the discussion earlier in this chapter, research literature has most often considered the roles of technology attributes, organizational learning attributes, and service attributes when studying HIT implementations (Cresswell & Sheikh, 2014; Venkatesh et al., 2011; Wass & Vimarlund, 2016; Westbrook et al., 2007). This study too will consider and examine a unique set of technology attributes, organizational learning attributes, and service attributes as predictors of EHR implementation success. The sections below discuss research studies and theories relating to the consideration of technology attributes, organizational learning attributes, and service attributes as predictors of information technology implementation success, leading to the development of hypotheses focusing on these attributes as predictors of EHR implementation success.

The Role of Technology Attributes in Implementation Success

Academic research has applied theories such as the Technology Acceptance Model (TAM), the Unified Theory of User Acceptance of Technology (UTAUT), and Roger's Innovation Diffusion Theory (IDT) to measure EHR acceptance by various stakeholders. The Theory of Reasoned Action (TRA) is considered as one of the foundational and influential social psychology theories on human behavior. The core constructs of this theory center around an individual's attitude towards performing the target behavior and the subjective norm perception that most people who are important to them think the individual should or should not perform the behavior in question (Fishbein & Ajzen 1975, p. 302). Grounded in sociology, IDT has been used for several decades to study a variety of innovations ranging from agricultural tools/technology innovations to OI (Tornatzky & Klein, 1982). Theory of Planned Behavior (TPB) extends TRA by adding the construct of perceived behavioral control which is the perceived ease or difficulty of performing the behavior. Social cognitive theory (SCT) is one of the most powerful theories of human behavior (Bandura, 1986). Compeau and Higgins (1995) extended SCT to the computer utilization context which has since been extended to information technology acceptance. Compeau and Higgins (1995) approached acceptance from the construct of job-related performance and personal consequence expectations, i.e. individual esteem and sense of accomplishment.

Technology Acceptance Model

Davis (1989) proposed TAM by extending TRA to predict technology acceptance and usage in a work environment. The model's objective was to improve understanding of user acceptance processes by providing theoretical insights into the successful design and implementation of IS. A second objective of the model was to provide a theoretical basis for a practical user acceptance testing methodology to enable system designers and implementers to evaluate proposed systems (Davis, 1985). Davis (1989) argued that the state of IS research at the time lacked empirically validated measures for predicting and explaining system use. The motivation for developing this model was to pursue better measures for pertaining and explaining IS use (Davis, 1989). The TAM incorporates diverse theoretical perspectives and presented a parsimonious model of adoption and use (Venkatesh et al., 2007). The model has been frequently cited in research in both IS and other fields, with well over 1,000 citations, thereby underscoring its impact in IS and beyond (Venkatesh et al., 2007). The model's constructs include *Perceived Usefulness (PU)* of the technology in enhancing an individual's job performance, *Perceived Ease of Use* (EU) of the technology and *Subjective Norm.* These attributes affect user's attitudes towards using an IS, and a user's attitude directly relates to a user's intention which will, in turn, determine the system usage of the technology. Research literature cites TAM as one of the most influential frameworks for predicting individual user's perceptions about IS use (Al-Adwan & Berger, 2015; AlJarullah et al., 2018; Chang & Hsu, 2012; Gagnon et al., 2014; Holden et al., 2012; Holden & Karsh, 2010; Hu et al., 1999; Kim et al., 2015; Melas et al., 2011; Steininger & Stiglbauer, 2015).

Perceived Characteristics of Innovating Framework

The perceived characteristics of innovating (PCI) framework is intended to be an instrument to measure the various perceptions that an individual may have of using an IT innovation. Moore and Benbasat (1991) developed the instrument as a tool for the study of adoption and diffusion of IT innovation within organizations. Moore and Benbasat (1991) approached acceptance from the perspective of perceptions of using the innovation, rather than perceptions of the innovation itself. The scholars argued that studies that had examined the primary characteristics of innovation had been inconsistent and differed from the perceptions of potential adopters. Moore and Benbasat (1991) stressed the need for well-defined constructs based on theory, and the operationalization of these constructs through measures with high degrees of validity and reliability. For this reason, Moore and Benbasat (1991) emphasized that studying interactions among perceived attributes of innovations helps in understanding the adoption/acceptance behavior of individuals. The scholars adapted the constructs presented in IDT to study individual technology acceptance in the context of adoption of personal work stations by individuals. PCI incorporates the following constructs: *Voluntariness*, *Relative Advantage*, *Compatibility*, *Ease of Use*, *Result Demonstrability*, *Visibility* and *Image*.

Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) conducted a comprehensive literature review pertaining to user acceptance of technology and used this to construct a unified framework of technology acceptance to explain the adoption and use of collaboration technology. Venkatesh et al. (2003) contended that IS research explaining user acceptance of new technology had resulted in a multitude of models. As a result, researchers were forced to pick and choose constructs across models. Venkatesh et al. (2003) saw a need for a review and synthesis in order to progress toward a unified view of user acceptance. By doing so, Venkatesh et al. hoped that future studies would need not have to search, collate and integrate constructs of existing theories that were similar in nature (Williams et al., 2011). This unified framework known as the unified theory of acceptance and use of technology (UTAUT), integrates eight distinct models of technology adoptiong and use, including TAM and incorporates four core determinants of intention and usage: *Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions* (Venkatesh et al., 2003). The UTAUT extends TAM among other models, by incorporating social influence and facilitating conditions. This model has provided a rich foundation for future research on technology adoption (Brown et al., 2010). The UTAUT provides a tool for managers needing to assess the likelihood of success for new technology introductions and helps them understand the drivers of acceptance in order to proactively design interventions targeted at populations of users that may be less inclined to adopt and use new systems (Sung et al., 2015). This model has been widely employed in technology adoption and diffusion research and has been cited at least 5,000 times in research literature (Williams et al., 2015).

Application of TAM, PCI, and UTAUT in the Healthcare Context

Wu et al. (2008) extended TAM to include variables connoting trust and management support and used this to investigate what determined acceptance of emergency reporting system by healthcare professionals. Pai and Huang (2011) integrated constructs from TAM and the Information System Success Model and proposed a new conceptual model to predict user's intentions to adopt a healthcare system. Saad et al. (2013) utilized TAM along with the Uses and Gratification theory (Ruggiero, 2000) to develop a framework for adoption and use of a telehealth portal. PCI has been used as the foundational model to measure perceived innovation attributes for eHealth innovations (Atkinson, 2007). Ornelas and Skaggs (2017) leveraged PCI constructs to identify the factors that influenced adoption of telehealth in a retail health clinic setting. Talukder et al. (2019) combined constructs of DOI and extended UTAUT models to investigate key facilitators of fitness wearable technology. Wu et al. (2011) argued that adoption of mobile healthcare technology required the consideration of perceived service availability and personal innovativeness towards IT use. Wu et al. (2011) extended the TPB and TAM to predict how healthcare professionals adopt mobile services. Several research studies have used TAM, PCI and UTAUT when investigating EHR implementations in several healthcare contexts (Carayon et al., 2011; Gagnon et al., 2014; Kowitlawakul et al., 2015; Morton & Wiedenbeck, 2009; Mullings & Ngwenyama, 2018; Tavares et al., 2018; Tavares & Oliveira, 2016; Tubaishat, 2018; Vitari & Ologeanu-Taddei, 2018; Wilkins 2009). Keeping in mind the importance of TAM, PCI and UTAUT from the above discussion, this study incorporates the following constructs from TAM, PCI and UTAUT in the hypotheses development: perceived ease of use, result demonstrability, and performance expectancy.

Ease of Use

Ease of use (EU) is defined in the TAM context as “The degree to which a person believes that using a particular system will be free of effort“(Davis, 1989, p. 320). In the context of using HIT, EU may refer to the ease of learning and mastering the system, clear and understandable system instructions, flexibility of the system, ease of performing tasks with the system, minimal extra workload, and ease of using the system during patient consultations (Gagnon et al., 2014; Holden & Karsh, 2010). Several research studies have explored the influence of EU on technology implementation success and found a positive association between ease of use and technology implementation success (Paré et al., 2006; Wu et al., 2008; Wu et al., 2007). The discussion above highlights the importance of ease of use in technology adoption and technology implementation success.

Based upon the above discussion, it is hypothesized as follows in this research study:

Hypothesis H1a: There will be a positive association between Ease of Use and Electronic Health Record implementation success

Result Demonstrability

Zaltman et al. (1973) referred to result demonstrability (RD) as “the more amenable to demonstration the innovation is, [and] the more visible its advantages are . . . the more likely it is to be adopted” (p. 39). Moore and Benbasat (1991) utilized this definition in the PCI model. They contended that RD sought to measure the tangibility of results when using an innovation including its observability and communicability. There is evidence in research literature of the use of the RD construct to predict IT implementation success by way of its adoption and use. Hebert and Benbasat (1994) assessed the impact of PCI, particularly RD, on nurse’s behavioral intent to use HIT. Hebert and Benbasat’s (1994) study revealed that the nursing staff felt it was important to demonstrate to their patients and others in the organization that the use of bedside terminal point-of-care technology led to beneficial outcomes. Liao and Lu (2008) utilized RD, among other constructs, to predict user’s intention of adoption and continued use of e-learning technology. Liao and Lu (2008) concluded that for users with prior e-learning experience, RD had significant direct effect on user’s intention of continued use. Karjaluoto et al. (2010) utilized RD as a construct in their framework to investigate the adoption of mobile banking technology among mobile banking users and non-users in the Brazilian context. Karjaluoto et al. (2010) found that RD along with other constructs helped explain 69% of the dependent variable variation among non-users. Chung et al. (2009) developed an enterprise resource planning (ERP) system success model to guide the successful implementation of ERP in the construction industry and identified RD to be a critical success factor in the implementation success. Other studies have utilized the role played by RD in influencing the successful implementation, adoption and use of eCommerce and Groupware technologies (Van Slyke et al., 2002; Van Slyke et al., 2004). The discussion above highlights the importance of result demonstrability in technology adoption and technology implementation success.

Based upon the above discussion, it is hypothesized as follows in this research study:

Hypothesis H1b: There will be a positive association between Result Demonstrability and Electronic Health Record implementation success

Performance Expectancy

Performance expectancy (PE) is defined in the UTAUT context as “The degree to which an individual believes that using the (technology) system will help him or her attain gains in job” (Venkatesh et al., 2003, p. 447). Venkatesh et al. (2003) viewed PE as the strongest measure of intention to use a technology. Numerous studies have investigated the impact of PE on IT implementation success by way of acceptance, adoption and use. Knutsen (2005) used PE as a construct to measure users’ attitudes towards consumer mobile services after its introduction to a population of users in the Danish context. Based on the results of his study, Knutsen (2005) concluded that PE was a strong determinant of user attitudes towards new mobile services. Brown, Dennis and Venkatesh (2010) presented a model integrating theories from collaboration research with UTAUT to explain the use of collaboration technologies such as Short Message Service (SMS). Brown et al. (2010) empirically validated their model through a survey of 500 users of SMS in Finland, one of the countries with a high penetration of mobile phones and high SMS use maturity. One of the significant conclusions of this study was that fit, i.e., the nature of task being performed played a role in users’ perceptions of PE and ultimately impacted their use of the technology. Holtz and Krein (2011) utilized UTAUT to assess nurse’s perceptions about the implementation of EHR technology at a hospital located in rural Michigan in the United States. Holtz and Krein (2011) identified that PE was a significant predictor on intention to use

EHR technology. Venkatesh et al. (2011) considered a modified version of UTAUT specifically for an EHR system adoption context by including *age*, *gender*, *experience* and *voluntariness of use* as moderators in the original UTAUT model. To test this model, Venkatesh et al. (2011) conducted a longitudinal field study in a private hospital that was in the process of implementing an EHR system. Venkatesh et al. (2011) concluded that PE explained 28% of the variance in each of the two dependent variables employed to measure EHR use in the revised model (versus 8% in the original). Ghalandari (2012) investigated the effects of PE and other constructs in the UTAUT model on the acceptance of e-banking services in Iran and found that it had a significant and positive impact on the behavioral intention to use e-banking services. Sung et al. (2015) utilized UTAUT constructs to assess mobile learning service adoption in South Korea. Based on the study results, Sung et al. (2015) determined that self-efficacy and social influence were meaningful antecedents to PE, which in turn had the most impact on positive behavioral intention to use mobile learning technology. The discussion above highlights the relevance of RD in technology adoption and technology implementation success.

Based upon the above discussion, it is hypothesized as follows in this research study:

Hypothesis H1c: There will be a positive association between Performance Expectancy and Electronic Health Record implementation success

The Role of Organizational Learning Attributes in Implementation Success

Past research studies have emphasized the importance of socio-technical aspects in evaluating HIT implementations (Ash et al., 2012; Cresswell & Sheikh, 2014; Cresswell et al., 2012; Hameed et al., 2012; Hsiao et al., 2011). Cresswell et al. (2012) argued that disruptive technological innovations in healthcare offered a unique opportunity to understand and evaluate the changing inter-relationships between technology and human/organizational factors.

Westbrook et al. (2007) characterized the delivery of safe and sustainable HIT systems for the future as a *wicked problem* due to its ill-defined and ambiguous nature related to strong moral, political and professional issues. Westbrook et al. (2007) theorized that the complex interaction issues that generally surface in an emergent social context require that implementation studies focus on the broader organizational and environmental contexts and processes. Theories such as the Sociotechnical Organizational Design theory, Social Shaping of Technology theory, and the HOT-fit and Normalization Process theory, which are being increasingly adopted to understand factors impacting HIT implementation success such as EHR implementation success, emphasize the consideration of organizational, human (socio) and environmental factors (such as competitors) (Cresswell & Sheikh, 2014; Westbrook et al, 2007).

Organizational learning capability (OLC) and organizational absorptive capacity (ACAP) are two organizational learning attributes that have most often been considered in past research studies pertaining to technology implementation success. This study also considers the association between these two organizational learning attributes and EHR implementation success.

Organizational Learning Capability and Technology Implementation Success

Past studies in research literature have investigated OLC as an organizational attribute associated with technology implementation successes (Ke & Wei, 2006; Khamis et al., 2014; Tucker et al., 2007). Organizational learning has been defined as the process through which organizations change or modify their mental models, rules, processes, or knowledge for maintaining or improving their performance (Chiva et al., 2014). According to Huber (1991) organizational learning is seen as a dynamic process which moves between different action levels, going from the individual action level to a group action level and from there to an organizational action level before circling back again. Huber (1991) emphasized that this type of organizational learning need not be conscious or intentional; an entity learns if, through its processing of information, the range of its potential behaviors is changed. Goh (1998) defined OLC as the ability of an organization to implement proper management practices, structure, procedure, and policies that facilitate and foster learning. Jerez-Gomez et al. (2005) stated that OLC should be able to create, acquire, transfer and integrate new knowledge, as well as modify existing behavior with a view to improving performance considering the new knowledge. Research concerning the various dimensions of OLC has evolved over a period of several years. Early models to measure OLC maturity involved learning curves and experience curves, and a number of patents and research expenditure budget for organizations (Jerez-Gomez et al., 2005).

Research scholars have approached technology implementation as the operationalization phase of an innovation (Cozijnsen et al., 2000; Vrakking, 1995; Zaltman et al., 1973). Several research studies have considered the association between OLC, technology innovation and technology implementation successes (Ke & Wei, 2006; Khamis et al., 2014; Mat & Razak, 2011; Robey et al., 2002; Tucker et al., 2007; Uğurlu & Kurt, 2016). Robey et al. (2002) studied the relationship between OLC and the implementation of a technology based innovation such as enterprise resource planning (ERP) implementation across 13 industrial firms. Following a comparative case study analysis, they concluded that OLC played a critical role in overcoming knowledge barriers associated with ERP implementation. Ke and Wei (2006) investigated the impact of OLC on implementation of Enterprise Resource Planning (ERP) systems in China and found OLC to impact implementation success. Tucker et al. (2007) researched the impact of OLC on the implementation success of a technology based process improvement plan undertaken in a hospital’s intensive care unit setting. Empirical analysis supported their hypothesis that the

Learn-how construct of OLC, which emphasized activities involved in operationalizing newer processes, was positively associated with the implementation success of the plan.

Building on Sundbo's theory of strategic management of innovation (Sundbo, 2001), Mat and Razak (2011) proposed a conceptual research model to investigate the relationship between OLC factors and technology innovation implementation success moderated by the knowledge complexity inherent in an innovation. Mat and Razak (2011) argued that OLC played a vital role in the entire innovation lifecycle starting with idea generation to successful implementation. Khamis et al. (2014) examined the effect of OLC on e-Business implementation success. Based on data collected from 110 organizations in the Malaysian banking and financial services industry, they found OLC constructs to have a significant positive association with successful e-Business implementation. Uğurlu and Kurt (2016) discussed the impact of OLC on product innovation successes in the Turkish manufacturing sector.

It can be inferred from the literature review above that OLC acts as an antecedent to OI, which in turn acts as a determinant of successful technology implementation. OLC has been demonstrated to have had a positive impact on new technology implementation success. This understanding is consistent with the findings from past academic research, which has found OLC to be one of the critical factors influencing newer technology and process implementation success (Ke & Wei, 2006; Khamis et al., 2014 Tucker et al., 2007). However, past studies have not explicitly examined the impact of OLC on EHR technology implementation success resulting in a research gap. This study fills the research gap by considering the impact of OLC on EHR technology implementation success, and thus makes a contribution to the literature in this field.

Based upon the above discussion, it is hypothesized as follows in this research study:

Hypothesis H2a: There will be a positive association between Organizational Learning Capability and Electronic Health Record implementation success

The Dynamic Capability Perspective

A discussion on learning in an organizational context is incomplete without introducing the concept of *dynamic capability* (DC). Due to the dynamic, fast-paced, and ever-changing business world of today, the concept of DC is very relevant and has been increasingly attracting the attention of researchers (Ambrosini & Bowman, 2009). Teece and Pisano (1994) proposed the DC view to overcome the shortcomings of the widely accepted resource-based view (RBV) of an organization. Knowledge, when understood as a strategic resource, is essential to a firm's ability to innovate and compete (Wang, 2013). Seen as a contemporary to the knowledge-based view (Grant, 1996), DC has its origin in organizational knowledge management. However, what sets it apart is its philosophy of not viewing knowledge as being *static* in nature. Instead, it seeks to explain organizational evolution and sustained success in a competitive environment as a result of viewing knowledge as *dynamic* and one that needs to be continually refreshed (Ambrosini & Bowman, 2009). Teece et al. (1997) forwarded the definition of dynamic capability as the firm's ability to integrate, build and reconfigure internal and external competences to address rapidly changing environments (p. 516). DC has been attracting the attention of researchers (Ambrosini & Bowman, 2009) to explain organizational evolution and sustained success in a competitive environment. This theory views a firm's knowledge as being *dynamic* and needing to be continually refreshed (Ambrosini & Bowman, 2009). This line of thought assumes significance from the realization that some of the once successful organizations of the world are struggling or failing down the line, possibly due to the lack of ability to adapt to the ever-changing business environment, by updating and reconfiguring internal and external competences to address rapidly changing environments (Ambrosini & Bowman, 2009).

According to Zollo and Winter (2002), DC is a learned and stable pattern of collective activity through which organizations systematically generate and modify operating routines in pursuit of improved effectiveness. Zahra et al. (2006) defined DC as the abilities to reconfigure a firm's resources and routines in the manner envisioned and deemed appropriate by its principal decision-maker. These definitions help highlight the fact that DC is built rather than bought, and that its use is a deliberate and intentional process (p. 918). The following sections discuss how DC has an impact on organizational absorptive capacity (ACAP) and how ACAP in-turn could impact technology implementation success.

Organizational Absorptive Capacity

Cohen and Levinthal (1989) conceptualized ACAP as a three-dimensional model composed of the ability to learn through the process of knowledge identification, assimilation and exploitation. Zahra and George (2002) proposed the construct of ACAP from a DC standpoint. Zahra and George (2002) defined ACAP as a set of knowledge-based capabilities embedded within an organization's processes including acquisition, assimilation, transformation and exploitation of knowledge. The scholars argued that while the importance of ACAP had been studied across multiple fields of strategic and technology management, its study remained difficult due to its ambiguity and diversity of its components, antecedents, and outcomes. Citing gaps in research literature pertaining to a consistent definition of ACAP, Zahra and George (2002) re-conceptualized ACAP as an embedded dynamic capability that influences a firm's ability to create and deploy the knowledge necessary to build other organization capabilities. ACAP is a DC pertaining to knowledge creation and utilization that enhances a firm's ability to gain and sustain competitive advantage (Ambrosini & Bowman, 2009). Zahra and George's (2002) framework defined ACAP as a set of organizational routines and processes by which firms acquire, assimilate, transform and exploit knowledge to produce dynamic organizational capability (p. 186). The framework distinguishes between potential ACAP and realized ACAP. Potential ACAP (PACAP) makes the firm receptive to acquiring and assimilating external knowledge. Realized ACAP (RACAP) refers to the firm's capacity to successfully leverage the knowledge that has been absorbed. The ratio of RACP to PACAP called efficiency factor provides an indication of the firm's ability to transform and exploit knowledge for profit generation.

Prior studies have demonstrated that ACAP contributes to an organization's innovation performance (Chen et al., 2009; Fosfuri & Tribó, 2008; Tseng et al., 2011). Scholars have studied dimensions of ACAP to better apply it to predict organizational innovation and success.

How Organizational Absorptive Capacity Differs from Organizational Learning Capability

Scholars have studied the relationship between ACAP and OLC with respect to the differences between them. Sun and Anderson (2010) conducted an extensive literature review to catalog the nature of this relationship. Based on the work of Winter (2000), they theorized that an organizational capability, such as organizational learning, refers to the set of activities carried out by a firm to produce outputs that determine its survival and prosperity within its current strategic setting. However, they argued that such outputs neither change the organization nor its strategic direction. Building on the work of prior scholars, Vera et al. (2011) provided a framework identifying boundaries of OLC, dynamic capability and knowledge management (KM). Vera et al. (2011) viewed OLC as a set of micro-processes and interrelationships concerning learning at the individual, group and organizational levels. By contrast, they presented dynamic capabilities as the ability to change routines and reconfigure routines to maintain competitive advantage. Sun and Anderson (2010) presented the view of ACAP as Teece at al. (1997), and Wang and Ahmed (2007) had proposed it, as a dynamic capability that reflects the ability of an organization to respond to *strategic* change by reconstructing its core capabilities (Teece et al., 1997; Wang & Ahmed, 2007). Winter (2003) categorized capabilities as a hierarchy using a mathematical metaphor of derivatives whereby zero-level operational capabilities pertain to how an organization earns its living now, the first derivative level of operational capabilities (i.e., change in the operational capabilities) are the dynamic capability of the organization, and the second derivative level has to do with a change in an organization's dynamic capabilities. Thus ACAP and OLC are not one and the same. In the next section, this study presents a literature review in support of developing a hypothesis that speaks to the association between ACAP and technology implementation success.

Organizational Absorptive Capacity and Technology Implementation Success

Several scholars have studied the impact of ACAP on the success of technology implementations. Gil et al. (2009) investigated the role ACAP played in the implementation of an ERP system in Turkey. Gil et al. (2009) applied the four constructs of ACAP namely acquisition, assimilation, transformation, and exploitation in examining the ERP implementation at three manufacturing firms in Turkey. Their study concluded that firms that achieved successful ERP implementation had invested heavily in these ACAP dimensions. Through increased ACAP, these firms had achieved their ERP implementation goals. Khosravi et al. (2012) approached the impact of an individual's ACAP on ERP implementation success. Khosravi et al. (2012) argued that individual-level ACAP assimilation directly impacted organizational level ACAP assimilation leading to ERP implementation success.

Khosravi et al. (2012) proposed a theoretical framework to investigate this relationship. Sharma, Daniel, and Gray (2012) investigated the ERP implementation success across nine medium-sized firms in India from an ACAP standpoint. Sharma et al.'s (2012) study supported prior findings linking increased ACAP with ERP implementation success. Another finding was the benefit of assimilating individual and organizational knowledge processes in the development of ACAP, and its impact on ERP implementation. In a similar study, Lee and Chen (2019) explored the influence of ACAP on Software Process Improvement (SPI) success. Lee and Chen (2019) hypothesized that ACAP had a positive influence on SPI success, and empirically validated this hypothesis in the context of 125 Chinese and Taiwanese organizations. Based on the study's findings, Lee and Chen (2019) concluded that ACAP played a fundamental role to effectively acquire, assimilate, transform and exploit SPI knowledge. Marabelli and Newell (2013) viewed organizational enterprise system (ES) implementation success as an ACAP challenge. The scholars argued that the addition of a process perspective provides a holistic view of how newer knowledge can successfully be assimilated in IT practice within an organization.

Marabelli and Newell (2013) supported their claims with a longitudinal and retrospective case study of a global organization headquartered in the United States and its implementation of a large-scale ES system. Kamal and Flanagan (2014) studied the impact of ACAP on technology implementation success in the context of medium sized enterprises in Malaysian rural construction industry context. Using a combination of deductive and inductive approach, they developed and validated their model to explain successful technology implementation and adoption in this setting. By using five rural construction SMEs as case studies Kamal and Flanagan examined these organization's attitude towards knowledge absorption and factors influencing their ability to use technology. Their findings highlighted certain factors that play the role of antecedents to ACAP and successful technology implementation in the rural construction environment.

The above review provided a broad perspective on the origin of ACAP and its role in successful technology innovation, acceptance as well as technology implementation. Scholars have widely applied ACAP to assess ERP implementations as well as its influence in organizational process improvement context. While these examples in literature exist there is not substantial evidence of empirical research explicitly examining the impact of dynamic capability or ACAP on HIT implementation success. Moreover, based on the literature review conducted, there have not been studies undertaken to investigate dynamic capability and ACAP's influence in HIT acceptance such as EHR. Therefore this research seeks to fill this gap in literature by analyzing and sharing findings in this regard.

Based upon the above discussion, it is hypothesized as follows in this research study:

H2b: There will be a positive association between an organization's Absorptive Capacity and Electronic Health Record implementation success

Service Attributes

Healthcare service is an intangible product and cannot physically be touched, felt, viewed, counted or measured like manufactured goods (Mohammad Mosadeghrad, 2013). Healthcare organizations are considered service providers (Djellal & Gallouj, 2007). Therefore, researchers must view HIT implementation success from a service perspective, and one that places emphasis on internal and external service relationships (Djellal & Gallouj, 2007). By contrast, healthcare has historically provided *products* or *goods* to consumers such as hospitalization, ambulatory care, medications and preventive care (Joiner & Lusch, 2016).

Vargo and Lusch (2004) defined services as the application of specialized competences (knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the entity itself (p. 2). Vargo and Lusch (2004) contended that a service-centered dominant orientation underscores collaborating with and learning from customers and being adaptive to their dynamic needs. Vargo and Lusch (2004) offered the service-centered view as follows:

> 1. Identify or develop core competences, the knowledge and skills to represent potential competitive advantage.
> 2. Identify other entities that could benefit from these competences.
> 3. Cultivate relationships involving customers in developing competitively compelling value propositions to meet specific needs.
> 4. Gauge marketplace feedback to improve offering to customer's thereby improving firm performance. (p. 5)

A central implication of service-dominant (SD) logic is the notion of *value co-creation* where organizations, customers and other actors co-create value through their service interactions with each other. Karpen et al. (2012) extended the SD logic context to define SD orientation to apply SD logic in practice at an organizational level. Karpen et al. (2012) defined SD orientation as "A co-creation capability, resulting from a firm's individuated, relational, ethical, empowered, developmental, and concerted interaction capabilities" (p. 21). Maglio and Spohrer (2008) extended the service-centering concept to service science and service systems. Maglio and Spohrer (2008) posited that service systems are value-co-creation configurations of: people, technology, value propositions connecting internal and external service systems, and shared information. It follows that service science is the study of service systems which are dynamic value co-creation configurations of collective resources (Maglio & Spohrer, 2008). Maglio and Spohrer (2008) saw technology as one of the pillars to this model, and cited IT outsourcing as an example of how individual, organization and technological competences come together to create value across the system.

Connection between Service-Dominant Orientation and Successful IS/IT Adoption and Implementation

Academic research has linked service-dominant (SD) orientation to strategic business practice and a means for competitive advantage (Karpen et al., 2012; Wilden & Gudergan, 2017). Wilden and Gudergan (2017) pointed out the variations in the definitions pertaining to SD orientation advanced by researchers and reiterated that that these definitions converge on the importance of resources and capabilities~~.~~

Several studies in research literature have examined the relationship between SD orientation of organizations and successful IS/IT implementations. Scholars have added to the body of SD literature by studying its impact on performance outcomes across multiple industry settings such as automotive retail, IT outsourcing, mobile online-to-offline technology adoption, self-service technology adoption, and supply chain management (Chen et al., 2015; Hilton et al., 2013; Karpen et al., 2015; Lusch et al., 2010; Maglio & Spohrer, 2008). Hilton and Hughes (2008) explored the co-production aspect of SD in the context of adoption of self-service technology by customers. Alter (2008) urged IS scholars to take a fresh approach by viewing systems as services and placing service and service metaphors as core metaphors of the field. Yan et al. (2010) proposed a model to strategically align SD orientation with IT implementations using the notion of service-oriented architecture (SOA). Lusch and Nambisan (2015) proposed broadening the notion of service innovation from its traditional view of tangible-intangible producer-consumer divide, and extended the SD body of research by advancing a view of innovation as a collaborative actor-to-actor network forming a service ecosystem. Lusch and Nambisan (2015) viewed IT as being an enabler in this ecosystem, by playing the roles of both an *operand* and an *operant* resource. Alias et al. (2018) applied SD orientation and Diffusion of Innovation (DOI) theories to investigate the adoption of Unified Communications and Collaboration (UC&C) technology. Lusch and Nambisan (2015) developed a research model based on select constructs from both factors and hypothesized that the combination of the two influences the successful implementation and adoption of UC&C technology by organizations.

Healthcare researchers have seen value in incorporating SD into healthcare service delivery. McColl-Kennedy et al. (2012) conducted an in-depth exploration of what healthcare customers do when they co-create value. Building on prior SD research and data collected through in-depth interviews, field observations, and focus groups, they proposed a healthcare Customer Value Cocreation Practice Styles typology. Porter (2010) questioned the fundamental premise of value addition in healthcare. Porter (2010) highlighted conflicting goals surrounding access to services, profitability and satisfaction that have contributed to a lack of clarity with respect to how value is defined. Porter and Lee (2013) called for a revamping of the underlying strategy for healthcare delivery to one that maximizes value for patients. Porter and Lee (2013) proposed a shift from the supply-driven framework which is organized around what physicians do, to one that is organized around what patients need. In their study, Porter and Lee (2013) provided a six-point value agenda to move towards a high-value healthcare ecosystem with HIT implementation being part of such agenda. The scholars predicted that ubiquity of medical records access to all parties involved, was one of the keys to a successful HIT platform.

Hardyman et al. (2015) discussed the perspective of value co-creation through patient engagement in micro-level encounters. Hardyman et al. (2015) maintained that every healthcare encounter from the patient's standpoint provided an avenue for multiple service encounters. Therefore to understand how value is co-created during these encounters, Hardyman et al. (2015) emphasized the need for further research focused on developing engagement strategies and patient-centricity. An avenue of investigation Hardyman et al. (2015) proposed ways to explore how value accumulates from *micro-level* value co-creation between patients and healthcare providers to a much broader healthcare organization's perspective, which value can be transported across settings. Zhang et al. (2015) proposed a model for the practical application of value co-creation in healthcare services. Zhang et al. (2015) discussed the nascent phase of SD orientation adoption in healthcare settings. Zhang et al. (2015) hypothesized that their model would help in improving service quality, by analyzing patient satisfaction ratings of healthcare service delivery and by incorporating such feedback into promotional strategies for service improvement. Joiner and Lusch (2016) took a critical view of the current state healthcare delivery from an SD standpoint. The scholars opined that the current-state is still focused on a goods dominant (GD) perspective of healthcare delivery. Joiner and Lusch (2016) highlighted the need for a change in approach from the traditional ways of patients' interactions with healthcare providers, to one that seamlessly integrates with everyday lives of patients. As examples of SD orientation in healthcare delivery, Joiner and Lusch (2016) cited technology implementations in healthcare organizations such as electronic health (eHealth) and mobile technology driven healthcare (mHealth). Joiner and Lusch (2016) underscored the need for healthcare providers to extend the value proposition of innovations such as EHR to the *health* *and well-being* of consumers. The scholars argued that this would truly transform healthcare from a GD to an SD function.

One the one hand, HIT advances continue to revolutionize how healthcare is being delivered to healthcare receivers and is being perceived by the stakeholders. At the same time, based on the discussion above, it is evident that a seminal shift in the definition of *value* and *service* in healthcare delivery is occurring. Both of the above have to be considered in the context of the ever-increasing healthcare service/delivery costs in the United States and the emergence of alternate forms of physician-patient encounters, such as those provided by national retailers like Walmart, CVS, and Walgreens (Porter & Lee, 2013). To address current issues associated with healthcare delivery, it is necessary to take the view of HIT implementations (such as EHR) as services employed by healthcare organizations with a SD orientation, to co-create value in the healthcare ecosystem. Healthcare organizations that embrace the service and value perspective will reap huge benefits in the future, and hospitals with private-practice physicians will have to learn to function as a team to remain viable (Porter & Lee, 2013). It is reasonable to conclude from the discussion in the preceding paragraphs that healthcare organizations that subscribe to the SD orientation will view EHR as an enabler to provide excellent end-to-end service-experiences. In addition, EHR implementation success will likely be impacted by its ability to deliver such experience based on the healthcare provider organization's SD orientation. In general, the concept of SD orientation applied to healthcare is relatively new (Joiner & Lusch, 2016). There has been limited empirical research on value co-creation, and the evolving literature in this field is mainly of a conceptual nature (Hardyman et al., 2015). Therefore, by proposing and testing a hypothesis linking EHR implementation success to the SD orientation of the healthcare provider organization involved in the EHR implementation, this research seeks to make a meaningful contribution to the existing body of literature.

Based upon the above discussion, it is hypothesized as follows in this research study:

Hypothesis H3: There will be a positive association between the Service-Dominant orientation of healthcare organizations implementing Electronic Health Records and Electronic Health Record implementation success

Dependent Variable - Electronic Health Record Implementation Success

Implementation success of technology in the domain of IS research is most often measured by how the technology/system performs during and after implementation- the premise is if the technology/system performs well and satisfies user expectations and functional requirements, it has been successfully implemented. Numerous studies in the IS/IT domain have used this approach in research literature.

Without a well-defined dependent variable, much of IS/IT research is purely speculative, but finding an appropriate dependent variable in IS/IT research has been a difficult quest (DeLone & McLean, 1992). Over the last few decades, academic researchers have studied multiple aspects of IS success from the technical, semantic and effectiveness levels (DeLone & McLean, 1992). With the aim of compiling and categorizing these success measures, DeLone and McLean (1992) conducted an expansive literature review and identified a taxonomy of IS success comprising of six major categories-*System Quality, Information Quality, Use, User Satisfaction, Individual Impact* and *Organizational Impact*. Based on the evolution of IS research, DeLone and McLean (2003) subsequently proposed a refinement to their model to include *Intention to Use* as another category of success measure.

Healthcare scholars have proposed models to measure HIT implementation success (Proctor et al., 2011; Yen et al., 2017). For instance, Proctor et al. (2011) proposed a heuristic, working taxonomy of eight conceptually distinct implementation outcomes to model implementation success—*acceptability, adoption, appropriateness, feasibility, fidelity, implementation cost, penetration, and sustainability*. Lack of acceptability has long been noted as a challenge in implementation (Davis, 1993). Based on this, Proctor et al. (2011) defined *Acceptability* as "The perception among implementation stakeholders that a given treatment, service, practice, or innovation is agreeable, palatable, or satisfactory". The referent of the implementation outcome ''acceptability'' (or the ''what'' is acceptable) may be a specific intervention, practice, technology, or service within a particular setting of care" (p. 67). Proctor et al. (2011) defined *Adoption* as "The intention, initial decision, or action to try or employ an innovation or evidence-based practice" (p. 69). An approach to measuring HIT implementation success involves HIT acceptance (Yen et al., 2017), and TAM is commonly applied to measure individual user acceptance (Yen et al., 2017).

Physicians' acceptance of EHRs is a critical factor for a successful implementation (Hackl et al., 2011; Steininger et al., 2014). Brevik and Khosrow-Pour (2005) performed a systematic review of research literature and synthesized that factors presented in UTAUT could be used to explain several dimensions of IS implementation success. Brevik and Khosrow-Pour's (2005) study found user acceptance to be an integral part of all streams of research pertaining to IS implementation success. Based on the above discussion pertaining to findings from research literature, it can be concluded that the notions of acceptance and adoption are two key indicators of implementation success of any information technology, including heath information technology.

In the context of EHR implementation, the *before* scenario in most cases is paper-based (i.e.) a scenario where EHR technology has not been in place prior to the implementation. In such cases, it would not make sense to measure the effectiveness of a paper-based process and compare it to the process after implementation because it is a proven fact that technology use is almost always more productive than manual work. Prior research studies have discussed the improvements/advantages gained by utilizing IS/IT systems (including EHR systems) over manual and paper-based processes (Agrawal, 2002; Bell & Thornton; Bhattacherjee, Hikmet, Menachemi, Kayhan, & Brooks, 2006; Chen et al., 2003; Elberg, 2001; Elder, Wiltshire, Rooks, BeLue, & Gary, 2010; Ewing & Cusick, 2004; Galewitz, 2011; Goetz et al., 2012; Kukafka et al., 2007; Linzer et al., 2000; Menachemi, Chukmaitov, Saunders, & Brooks, 2008; Menachemi & Collum, 2011; Menachemi, Powers, & Brooks, 2009; Miskulin et al., 2009; Mildon & Cohen, 2001; Pathman, Williams, & Konrad, 1996; Thakkar & Davis, 2006; Tierney, Miller, Overhage, & McDonald, 1993; Virapongse et al., 2008; Wang et al., 2003; Zaroukian & Sierra, 2006; Zhang, Yu, & Shen, 2012). It is therefore superfluous to seek to establish a baseline metric with paper-based records when studying the implementation of EHR.

Past studies from research literature pertaining to technology implementations in general and HIT implementations in particular have most often adopted user attitudes, user satisfaction, and intention to use as measures of acceptance, adoption/implementation success, i.e., as the dependent variables (Chaudoir et al., 2013; Phichitchaisopa & Naenna, 2013; Yu & Qian, 2018). In this study too, user attitudes, user satisfaction, and intent to use have been adopted as the dependent variables in the research model for measuring EHR implementation success.

User Attitudes

User attitudes could be defined as an individual's overall affective reaction to using a system (Venkatesh et al., 2003). Fishbein and Ajzen (1975) defined attitude toward use as an "individual's positive or negative feelings (evaluative effect) about performing the target behavior" (p. 216). Researchers have attempted to understand factors influencing pre and post implementation attitudes with respect to technology implementations (Holden, 2011; Moody et al., 2004; Morton & Wiedenbeck, 2009; Wright et al., 2010). Morton and Wiedenbeck (2009) examined physician attitudes prior to EHR implementation in an academic healthcare system by developing and empirically validating a research framework. Morton and Wiedenbeck (2009) measured user attitude towards EHR as a dependent variable potentially influenced by several technology and organizational constructs. The results showed that their chosen independent variables explained 73% of variance in attitude. The study found a strong positive correlation between physician involvement in EHR implementation and their attitudes towards EHR use.

Other researchers have approached research on user attitude towards HIT from a social network and norm perspective (Aldosari, 2004; Anderson, 2002; Dansky et al., 1999; Greenhalgh et al., 2004). As part of a multi-phase research endeavor examining the implementation of EHRs at a medical school of a large regional university and a large multi-physician practice, Seeman and Gibson (2009) employed a combination of TAM and TPB models to predict EHR acceptance by physicians. In this study, Seeman and Gibson (2009) found that user attitude was one of the constructs which played a highly significant role in explaining EHR acceptance. Morton (2008) studied individual and sociotechnical factors that may contribute to physician's attitude towards EHRs. Factors with the strongest positive effect on user attitude towards EHRs were physician involvement and perceived usefulness. Based on the findings of the study, Morton (2008) argued for strong physician involvement and leadership in the EHR implementation process to ensure implementation success. Based on the above discussion, this study has adopted user attitude as one of the dependent variables in the research model for measuring EHR implementation success.

User Satisfaction

User satisfaction has often been used as a success measure in research studies involving specific IS/IT system implementations (Jarvenpaa et al., 1985; Lucas, 1978; Sanders 1984). User satisfaction is the user's overall level of satisfaction during their interactions with an IS or IT (Petter et al., 2008). User satisfaction is regarded in research literature as one of the common measures of IS implementation success (Seddon & Kiew, 1996). User satisfaction with HIT systems (such as EHR) has been examined in research literature from a wide range of perspectives, including training, IT infrastructure capability, and successful performance of essential clinical and non-clinical tasks (Afnan & Chadrasekaran, 2015; Holanda et al., 2012; Unni et al., 2016).

Pfoh et al. (2012) conducted a cross-sectional survey of healthcare providers who transitioned from an older to a newer EHR at six academic, urban ambulatory medical practices. Pfoh et al. (2012) assessed several domains including satisfaction with the transition, current use of other forms of IT, general work perceptions, methods for completing daily clinical tasks, demographic information, and medical practice characteristics. The research study found that user satisfaction with the transition, availability of certain system features, and adequacy of technology support was significantly associated with satisfaction with the new EHR system. Holden et al. (2012) measured nurses' acceptance of a bar coded medication administration (BCMA) system through a cross-sectional survey of registered nurses at an academic pediatric hospital that had recently implemented BCMA. Holden et al. (2012) modeled a framework based on TAM, TAM2, and TAM3, by utilizing nurse's satisfaction (user satisfaction) with BCMA as a construct for predictor of acceptance. Holden et al. (2012) found that social influence from patients and families, perceived usefulness for patient care, and perceived ease of use best predicted nurse's satisfaction (user satisfaction). Based on their results, Holden et al. (2012) concluded that success with BCMA implementations is best assessed from an end-user acceptance through measures such as user satisfaction. Based on the above discussion, this study has adopted user satisfaction as one of the dependent variables in the research model for measuring EHR implementation success.

Intention to Use

The intent-behavior relationship has been extensively studied in research literature (Davis, 1989; Venkatesh et al., 2003). Behavioral intention to use is defined as "a measure of the strength of one's intention to perform a specific behavior, that is, use an information system" (Fishbein & Ajzen, 1975, p. 288). Based on its increased relevance to predict IS success, as well as it being a procedural antecedent to the *Use* construct, DeLone and McLean (2003) enhanced the IS Success model to incorporate an *Intention to Use* perspective. Researchers have often utilized the *Intention to Use* construct to predict IS/IT implementation success and adoption and acceptance of HIT systems including EHRs (Al-Adwan & Berger, 2015; AlJarullah et al., 2018; Bossen et al., 2013; Gagnon et al., 2014 Holden et al., 2012; Jahanbakhsh et al., 2018; Kim et al., 2015; Steininger & Stiglbauer, 2015). Al-Adwan and Berger (2015) utilized behavioral intent to use EHR as a measure of physician's acceptance of EHR. Al-Adwan and Berger (2015) found that physician's perception of ease of use significantly influenced their behavioral intention to use EHRs. Gagnon et al. (2014) conducted a similar study to measure physician's intention to adopt EHR in Canada, by operationalizing physician's EHR acceptance as their behavioral intent to use the system. Their research model was based on an integrative approach using TAM and the theory of interpersonal behavior (TIB). Based on the results of the study, Gagnon et al. (2014) concluded that the constructs of perceived ease of use, perceived usefulness, and self-efficacy had significant overall effect on physician's behavioral intention to use EHRs. Amoako-Gyampah and Salam (2004) extended the TAM model and applied it in an ERP implementation environment. Amoako-Gyampah and Salam (2004) identified managerial interventions such as communication and training influenced behavioral intention to use the technology. Based on the above discussion, this study has adopted *Intention to Use* as one of the dependent variables in the research model for measuring EHR implementation success.

Summary

This chapter presented a review of literature pertaining to IT implementations, HIT innovations, EHR benefits and barriers to successful implementations, followed by specific theories pertaining to technology attributes, organizational learning attributes and service attributes that can help predict EHR implementation success. Ease of use, result demonstrability and performance expectancy have been documented in prior research as vital technology attributes. Similarly, this literature review established OLC and ACAP as two key organizational learning attributes that can influence EHR implementation success. An emerging body of research now views healthcare delivery as a service and has identified eHealth and mHealth implementations as examples of SD orientation in healthcare delivery. Based on this literature review and the research model presented in chapter 1, this chapter presented a set of hypotheses for this research study. It is proposed to test these hypotheses through data collection and statistical analyses. In the next chapter (chapter 3), the research methodology and proposed statistical analyses will be discussed.

CHAPTER 3

RESEARCH METHODOLOGY

Introduction

This chapter discusses the research methodology used in the research study. Data collection steps followed by an overview of statistical analysis are presented. This forms the basis of results and discussion of findings presented in subsequent chapters.

Data Collection

The data collection methodology used in this study was a questionnaire survey based on a Likert Scale. Questionnaires are appropriate for gathering quantitative data and explaining how many people hold a particular opinion (Kitzinger, 1995). Questionnaires also accurately document norms, identify extreme outcomes, and delineate associations between variables in a sample (Gable, 1994). A high-quality survey follows appropriate research design, sampling procedures, and data collection methods (Pinsonneault & Kraemer, 1993).

Questionnaire Survey Design

The items (questions) in the instrument (questionnaire survey) were borrowed from past research studies (after obtaining the required permissions). The verbiage of some items was modified to suit the current research context. The advantage in using items from past studies is that it is likely that they would have been already tested for different forms of validity (Ahrens & Pigeot, 2014; Hyman et al., 2006).

The first section of the instrument contained questions pertaining to demographics to gain an understanding about the demographic profile of the respondents. Some of the demographic questions were multiple response questions wherein the respondents were requested to select all answer choices that applied, while others were single answer choice questions. Four distinct sections of the instrument included items specific to the independent and dependent variables considered in this study, namely technology attributes, organizational learning attributes, service-oriented attributes, and EHR implementation success.

Technology attributes were assessed using constructs for ease of use, result demonstrability and performance expectancy. Previously developed instruments by Morton and Wiedenbeck (2010), Moore and Benbasat (1991), and Venkatesh et al. (2003) respectively were used to measure these constructs. Organizational learning attributes were assessed using constructs for organizational learning capability (OLC) and organizational absorptive capacity (ACAP). Sánchez et al. (2010) developed an instrument to measure OLC which was utilized in this study. Items for measuring ACAP was obtained from Pavlou and El Sawy (2006). Service attributes were assessed using the construct for service-dominant orientation. Instruments by Chandy and Tellis (1998), Deshpandé et al. (1993), and Hurley and Hult (1998) were utilized for this purpose. EHR implementation success was measured through user attitudes, user satisfaction, and intention to use with instruments originally developed by Seeman and Gibson (2009), and Holden et al. (2012). The researcher sought and obtained approvals from the instrument's authors prior to their inclusion in the study. Appendix A provides a summary of items and their sources.

The respondent profile used in this study consisted of Information Technology (IT) consultants, management consultants, project managers, physicians, nurses, healthcare facility administrators, and healthcare facility staff (such as pharmacists and physical therapists) who have been part of an *EHR experience* for a period of one year or more during the last five years. *EHR experience* is defined in this study as having been involved with the implementation, use, and maintenance of EHR during the stated period.

Sampling Procedure / Data Collection Method

The survey instrument was administered electronically, using the online survey tool Qualtrics™. Data collected via the website was exported as a flat file. Then analysis of the data was conducted using the statistical software, SPSS and R.

In healthcare research, it often becomes necessary to identify groups or associations whose members have common characteristics and who meet the respondent profile requirements.

The weblink to the instrument was made available to members of three professional groups in the manner described below:

1. Vidant Health - the teaching hospital for the Brody School of Medicine at East Carolina University:

   The IT department at Vidant comprised of approximately 200 employees who were involved with the implementation, use and/or maintenance of EHR. This professional group was chosen because of two reasons: (a) Vidant Health was involved in the implementation, use and maintenance of EHR which is the subject matter of this study and (b) relatively easy access to the facility through academic connections.

   The researcher communicated with the Chief Technology Officer (CTO) of Vidant Health and explained the context of the research to him. After formal IRB approvals were obtained, the CTO distributed the link to the electronic survey through an email blast to all employees informing them about the opportunity to participate in the study.

2. Members of professional healthcare association at the American Health Information Management Association (AHIMA) conference:

   Founded in 1928, AHIMA is a premier association of Health Information Management (HIM) professionals worldwide. AHIMA currently serves 52 affiliated component state associations and more than 103,000 health information professionals, is the leading authority on HIM knowledge, and is widely respected for its esteemed credentials and rigorous professional education and training ("AHIMA Who We Are", 2019).

   The AHIMA Foundation is a charitable affiliate of AHIMA which provides resources to support continuous innovation and advances through research, leadership and educational scholarship opportunities in HIM ("The AHIMA Foundation", n.d.). The foundation's research network enhances the importance of research within the HIM profession and strives to add to the HIM body of knowledge ("The AHIMA Foundation", n.d.). Due to AHMIA's leadership in furthering HIM and corresponding research, and the potential professional diversity among its members, the researcher sought to survey AHIMA members for this study. The researcher contacted the AHIMA foundation to obtain formal permission to distribute the electronic survey to its members.

   After obtaining both the IRB and the AHIMA Foundation's approvals, the electronic survey was posted across several HIM 'Engage online communities' on AHIMA's online portal. The purpose of AHIMA's 'Engage online communities' is to strategically align content and forums that caters to areas of importance to HIM professionals. The community's intent is to provide an opportunity for students and researchers to discover and disseminate useful information about the health information professions ("AHIMA Who We Are", 2019).

The researcher examined and selected communities whose members matched the potential respondent profile. Based on this review, the following Engage communities were identified: Care Coordination and Management, Clinical Documentation Improvement, Coding, Classification & Reimbursement, Confidentiality, Privacy & Security, Data Analytics, Health Information Technologies & Processes, Healthcare Leadership and Innovation, and Long-Term Post-Acute Care. As of August 2019, the total number of registered members across these communities were more than 19,500. It is likely that members were registered with multiple forums. Hence the total number of distinct members eligible to participate in the survey was lower than 19,500. The researcher attended the AHIMA annual conference held in Chicago in Fall 2019, to network with and verbally solicit survey participants who would have then responded to the survey posted via the Engage forums.

The following sentence is being added to the dissertation per AHIMA Foundation's policy: *It is to be noted that Information obtained through the survey posted by visiting an AHIMA Engage online community does not represent the views or opinions of AHIMA, the AHIMA Foundation, or AHIMA membership, and is not sponsored or endorsed by AHIMA unless otherwise stated*.

3. The Healthcare Information and Management Systems Society, Inc.:

(HIMSS) is a global advisor and thought leader supporting the transformation of health ecosystem through information and technology with a membership of over 80,000 individuals, 480 provider organizations, and 650 health service organizations ("About HIMSS", n.d.). The Greater Illinois Chapter (GIC) of HIMSS comprises of experienced healthcare professionals from the greater Illinois area working at hospitals, corporate health systems, consulting firms, vendor organizations, universities, and a wide variety of other organizations ("About GIC HIMSS Chapter", n.d.). Considering HIMSS's role in shaping global healthcare, physical proximity to the Greater Illinois Chapter of HIMSS, as well as a close match of its member's profiles with the desired survey respondent profile, the researcher chose to distribute the survey to this chapter.

The researcher contacted the President of GIC HIMSS and obtained permission to distribute the electronic survey. After obtaining formal IRB approvals, the survey was distributed to approximately 3,000 GIC HIMSS via the chapter's newsletter.

The electronic survey was made available to respondents for a period of five months between August 2019 and December 2019.

Protection of Human Subjects / Institutional Review Board

The initial research proposal was reviewed and approved by the Institutional Review Board (IRB) at Indiana State University, which is the body concerned with, among other duties, protecting the privacy and confidentiality of the study participants. Supporting documentation such as the Informed Consent document and survey questionnaire document were submitted. After obtaining the IRB approval (Appendix B) and site approvals at Vidant, AHIMA and GIHIMSS, participants were invited to visit the electronic survey site using the weblink provided to take the survey, should they choose to do so. The first page of the survey was the Informed Consent (Appendix C) description, which provided participants with an overview of the study and their rights and risks should they choose to respond to the survey. After reading the informed consent, it would be possible for one to choose not to participate in the survey voluntarily. To maintain respondent confidentiality and anonymity, Internet Protocol (IP) address tracking was disabled within the Qualtrics ™ online survey tool.

Statistical Analysis Overview

Statistical methods were used to analyze the survey responses. Due to the presence of latent variables in the research model, the advanced statistical method Structural Equation Modeling (SEM) was used. The software used for the statistical analyses were R and SPSS.

Sample Size Validation

An adequate sample size is an important consideration when using statistical methods in order to obtain statistical significance and also to allow for generalizability of the results. In studies involving use of the SEM statistical method, sample size ranges from 30-460 (Wolf et al., 2013). Nunnally and Bernstein (1994) recommend 20-30 participants per independent variable in the survey instrument as the sample size when using the SEM method, in order to increase replicability of results. Hoyle and Gottfredson (2015) recommend a sample size of more than 200 to achieve desired levels of power for models of typical complexity when using the SEM method.

Cochran’s formula (1977) has been used by several scholars to model sample size calculations. The use of Cochran’s formula ensures that statistical tests based on a certain sample size do not lack power in case of a small sample size, or have excessive power in case of a big sample size (Nunkoo, 2018). It also provides an appropriate means of ensuring that the results of inferential statistics do not provide misleading conclusions for a given confidence level or margin of error (Nunkoo, 2018). Many studies in academic research literature involving the SEM method have used a sample size calculated with Cochran's formula (Moshki et al., 2013; Nikookar et al., 2015; Nunkoo, 2018; Sheikhy & Hamzeie, 2015; Vasilenko, & Khazieva, 2016; Wah Yap et al., 2012), and the same approach was adopted by this study.

Factorability

The Kaiser-Meyer-Olkin (KMO) test (Kaiser, 1970) is used to measure and validate sampling adequacy. KMO is a test that indicates how suitable the data is for factor analysis. The test measures sampling adequacy for each variable in the model and the complete model. A rule of thumb for interpreting the statistic is KMO values between 0.8 and 1 indicate that patterns of correlations are relatively compact and so factor analysis should yield distinct and reliable factors (Field et al., 2012). Values greater than 0.9 are superb, between 0.8 and 0.9 are great, between 0.7 and 0.8 are good, between 0.5 and 0.7 are mediocre (Hutcheson & Sofroniou, 1999). The outcome of the Kaiser-Meyer-Olkin (KMO) test for the data in this study will be presented in chapter 4.

Bartlett's Test of Sphericity checks to see if there is a certain redundancy among the variables being measured which can be summarized with a fewer number of factors, by verifying if the population correlation matrix resembles an identity matrix (Field et al., 2012). The null hypothesis of the test is that the variables are orthogonal, (i.e.) not correlated. The alternative hypothesis is that the variables are correlated enough to where the correlation matrix significantly diverges from the identity matrix. Bartlett's test must be executed to determine if its result is significant (i.e.) the correlations between variables are significantly different from zero. Any variables found to have very low correlation to make analysis meaningful will need to be excluded. Multicollinearity and singularity must also be considered to determine if any variables are highly correlated so that variables exhibiting multicollinearity can be excluded. Exploratory factor analysis (EFA) was performed as an additional due diligence measure to determine if variables used for analysis could be narrowed down to a smaller count. The outcome of the Bartlett's Test of Sphericity, multicollinearity/singularity, and EFA for the data in this study will be presented in chapter 4.

Reliability Analysis

Reliability implies that a measure (in this case the survey questionnaire) should consistently reflect the construct it is measuring (Field et al., 2012). Reliability is the consistency or repeatability of measures; a measure is considered reliable if it produces the same result over and over again (Trochim & Donnelly, 2001). Internal consistency reliability is a type of reliability that is used to assess the consistency of results across items within a test (Trochim & Donnelly, 2001). In the context of surveys, the reliability of the instrument is judged by estimating how well the items that reflect the same construct yield similar results (Trochim & Donnelly, 2001). Internal consistency reliability is typically calculated using Cronbach's Alpha, a common measure of test and scale reliability (Cortina, 1993; Nunnally et al., 1967; Santos, 1999; Trochim & Donnelly, 2001). Cronbach's alpha was derived for the independent and dependent variables in order to gather information regarding measurement stability and internal consistency of the instrument.

Introduction to Structural Equation Modeling

SEM is the statistical method of choice when latent variables are employed in a research study (Hox & Bechger 1998; Tarka, 2018). SEM is a useful methodology for specifying, estimating, and testing hypothesized interrelationships among a set of substantively meaningful variables (Bentler, 1995). SEM has been described as an extension of multiple regression analysis (Schumacker & Lomax, 2010) or a combination of multiple regression and exploratory factor analysis because SEM is more of a confirmatory technique (Ullman & Bentler, 2003). Essentially, an SEM is composed of a measurement model and a structural model (Keith, 2006). SEM tests correlations between variables to determine if hypothesized directional relationships exist within a theory or model, and if the hypothesized model is a good fit to the observed data. (Schreiber et al., 2006; Schumacker & Lomax, 2010). Specifically, SEM is able to produce a clear and explicit result of the strength of the mathematical relationship contained in the theory or model (Kellar & Kelvin, 2013; Olobatuyi, 2006). The measurement model examines connections between observed variables and their underlying latent variables by means of confirmatory factor analysis (CFA). The structural model inspects the relationships among latent variables. An SEM model utilizes path diagrams to schematically represent interrelations among observed and latent variables (Byrne, 2010).

In SEM, exogenous variables (independent variables determined by causes outside the causal model) such as organizational absorptive capacity may have direct effects on other variables such as organizational learning capability, where the effect of one variable on another is not mediated by any other variable (Olobatuyi, 2006; Streiner, 2005). The endogenous variable (dependent variable) of this study was EHR implementation success measured through the constructs of user attitudes, user satisfaction, and intention to use.

According to Schumacker and Lomax (2010), SEM, unlike path analysis which is limited to observed variables, includes latent variables in the theoretical model. Byrne (2010) added that latent variables, which are not measured directly, but, instead, are linked to other observable variables, make measurement of the latent variable possible. For example, in this study, technology attributes were indirectly observed through the constructs of ease of use, performance expectancy and result demonstrability. Thus in this study, technology attributes were a measurement of the observed variables also called measured variables or indicators of the underlying construct which they represent using the logic suggested by Byrne (2010) and Schreiber et al. (2006).

SEM may be performed in a model generating approach, as in this study. According to Schumacker and Lomax (2010), in the model generating approach, a theoretical model (such as the research framework for this study) is formulated by researchers and then tested to determine if the data fit the model. If the data do not fit the hypothesized model, structural paths are added or deleted to arrive at the best fit model (Schumacker & Lomax, 2010).

Use of SEM methodology has gained in use due to four strengths (Schumacker & Lomax 2010, Wilson 2018). Firstly, researchers are aware of the need to use multiple observed variables within their analysis, especially when seeking to model complex phenomenon such as healthcare technology adoption. Secondly, SEM has the ability to account for measurement error of each model construct, therefore increasing validity and reliability of observed scores from measurement instruments (Grapentine, 2000; Schumacker & Lomax, 2010; Ullman & Bentler, 2003; Wilson, 2018). Thirdly, Schumacker and Lomax (2010) mentioned a maturity of SEM methodology, where researchers are able to analyze more advanced theoretical SEM models such as multilevel SEM modeling, causing less reliance on basic statistical methods. Finally, advanced software (e.g., R, SAS etc.) is becoming available to facilitate SEM analyses (Schumacker & Lomax, 2010; Wilson, 2018).

The SEM modeling approach can be accomplished in four steps and the same was followed in this study (Bollen & Long, 1993; Huang, 2010). The four steps are as follows: (a) model specification, (b) model identification, (c) model estimation and evaluation, and (d) model modification and re-specification (as needed and if needed). These four steps are discussed in detail next.

Model Specification

In model specification, the researcher fully specifies what variables will be tested prior to the initiation of any analysis (Schumacker & Lomax, 2010; Wilson, 2018). A thorough understanding of the literature is necessary in order to avoid a specification error (Wilson, 2018). Olobatuyi (2006) defined a specification error as a "mistake committed by researchers when deciding upon the causal model" (p. 46). For example, specification errors occur when omitting relevant exogenous variables or when including irrelevant exogenous variables within the theoretical model (Olobatuyi, 2006). As in other studies (Wilson, 2018), this dissertation employed extensively studied research frameworks and an extensive and thorough literature review to support the use of the variables postulated in the theoretical model. Furthermore, each variable chosen for the model had already faced extensive literary examination and assessment in prior studies.

Model Identification

Model identification is done by comparing the number of available information items (i.e. variances and covariances) with the number of free parameters to be estimated (Huang, 2010). An SEM model should be "identified", meaning there "should be the same number of knowns (correlations), and unknowns (structural coefficients)" (Olobatuyi, 2006, p. 89). The researcher determines if the model is overidentified, under-identified, or just-identified (Olobatuyi, 2006). According to Olobatuyi, an over-identified model occurs when the known information (variances and co variances) of the data set are less than the number of structural paths. In an over-identified model, there is more information than needed to estimate the parameters (Olobatuyi, 2006). For example, if there exists four correlations but only three structural coefficients to estimate, the model would be considered over-identified and the unique estimation of all the parameters of the model will be impossible (Olobatuyi, 2006). Another identification problem exists when a model is under-identified (or not identified), meaning that there are too many unknowns to be solved or too many structural paths than variances and covariances (Streiner, 2005). Olobatuyi (2006) described an under-identified model as one that "contains insufficient information for the purpose of obtaining a determinate solution of parameter estimation" (p. 51). An under-identified model may challenge the researcher by causing it to be impossible to estimate the structural coefficients in the equation, resulting in estimates that are inconsistent (Olobatuyi, 2006; Streiner, 2005; Wilson, 2018).

A just-identified model is one that has an equal amount of variables to structural paths to be estimated, resulting in no paths deleted (Olobatuyi, 2006). Schumacker and Lomax (2010) further explained that a model is just-identified if "all the parameters are uniquely determined because there is just the amount of information on the matrix" (p. 57). Generally, if a model is just-identified or over-identified, then the model is considered identified.

Schumacker and Lomax (2010) provided three methods to avoid identification problems, which were used in this dissertation study. First, within the measurement model, "either one indicator for each latent variable must have a factor loading fixed to 1, or the variance of each latent variable must be fixed to 1" (p. 58). Second, Schumacker and Lomax (2010) warned against using a reciprocal or non-recursive model. A reciprocal or non-recursive model contains "feedback loops" (p. 59) where two latent variables are reciprocally related. Third, Schumacker and Lomax (2010) encouraged the use of a parsimonious model, with a minimum number of parameters that only includes variables that have been well proven in the literature (Wilson, 2018).

Model Estimation and Evaluation

The next step in the SEM method is the calculation of correlation coefficients and determining structural coefficients between variables. The extent that two or more variables are related to one another is expressed as a correlation coefficient (Olobatuyi, 2006). Moreover, Olobatuyi (2006) stated that the correlation coefficient is a “measure of the direction and strength of a linear relationship” (p. 27). A separate regression calculation must be performed for each exogenous variable that exerts either a direct effect or indirect effect on the endogenous variable. Structural coefficients and multiple correlation coefficients may be calculated using computer software (SPSS software was used for this purpose in this study). The model is then estimated using the maximum likelihood with robust standard errors (MLR) method (which is built into R software) with standard errors and a chi-square ($\chi 2$) test statistic robust to non-normality and non-independence of observations.

The model thus estimated is evaluated using three distinct means. First, the model’s degree of fit is evaluated through multiple fit indices recommended by previous researchers. Second, the model is inspected with respect to the feasibility of its parameter estimates. Finally, the relevant squared multiple regressions (R^2) associated with the model are reported. Table 1 is a summary of the common fit indices used to evaluate model fit in SEM and the values of the fit indices which signal an acceptable model fit.

Table 1 Common Fit Indices to Evaluate SEM Model.

Fit Index	Criterion	Literature Reference
Chi-square ($\chi 2$) test	Non-significant value*	Kline (2005)
Bentler comparative fit index (CFI)	Value >= 0.90	Kline (2005); Wang and Wang (2012)
Tucker Lewis Index (TLI)	Value >= 0.90	Schumacker and Lomax (2010)
Root mean square error of approximation (RMSEA)	Value < 0.08	Kenny (2015); Kline (2005); Wang and Wang, 2012; Schumacker and Lomax (2010)
Standardized root mean square residual (SRMR)	Value < 0.08	Hu & Bentler (1999); Wang and Wang (2012)
Chi-square/degree of freedom ratio ($\chi 2$/df ratio)	Value < 5 for good fit	Wheaton, Muthen, Alwin, and Summers (1977); Hallquist (2017)

It should be noted here with respect to the $\chi 2$ test that this test is sensitive to sample size in the sense that large samples frequently return significant $\chi 2$ statistics despite adequate model fit (Kline, 2016). Kline (2005) indicated that the $\chi 2$ test "may lead to rejection of the model even though differences between observed and predicted covariances are slight" (p. 136). Therefore, the ratio of $\chi 2$ to degrees of freedom test is incorporated to compensate for $\chi 2$ sensitivity to sample size (Kline 2016, 2005).

Model Modification and Re-specification

The final step, according to Schumacker and Lomax (2010) and Wilson (2018), is model re-specification wherein the relationships in the initial model are considered for modification as needed. An SEM model is considered good when the data produces a model fit (as measured by the fit indices). Re-specification is done for poorly fitting models with the aim of finding a better fitting model (MacCallum et al., 1992). There are two commonly used techniques of performing the model modification. The Lagrange Multiplier technique estimates the decrease in the $\chi 2$ test statistic that would occur if a parameter were to be freely estimated (Worthington & Whittaker, 2006). The second technique approximates the amount by which the overall $\chi 2$ would increase if a specific freely estimated path were fixed to zero (Kline, 2005). A perfect model will have residuals of zero and a poorly fitted model would be evaluated by how many standard deviations the residuals are from zero (Schumacker & Lomax, 2010; Wilson, 2018),

If the fitness evaluation is unfavorable, the model must be re-specified and the fit evaluation process repeated. When the best fitting model is eventually found in this manner, it becomes the baseline model with which to create the full latent variable model, to produce completing models, or to respond to the research questions.

Summary

This chapter provided an overview of the research methodology, respondent profile, data collection process and statistical methods utilized in this study. The results of statistical analysis and hypothesis testing will be discussed in the next chapter.

CHAPTER 4

RESULTS

Introduction

This chapter discusses the statistical analyses and results. The primary aim of this study was to investigate the association between a select set of technology attributes, organizational learning attributes, and service attributes on Electronic Health Record (EHR) implementation success. The analyses were conducted to evaluate the posed research questions derived from the specific aims:

1. Can EHR implementation success be predicted by a select combination of technology, organizational learning and service attributes?
2. Do ease of use, result demonstrability and performance expectancy impact EHR implementation success?
3. Does organizational learning capability impact EHR implementation success?
4. Does organizational absorptive capacity impact EHR implementation success?
5. Does a service-dominant orientation impact EHR implementation success?

Sampling Plan, Sample Size and Statistical Power

When it is possible, random or probability sampling is recommended as the method of choice for respondent selection because randomization reduces biases and allows for the extension of results to the entire sampling population (Godambe 1982; Smith 1983; Snedecor

1939; Topp et al., 2004). However, random sampling is not always possible and not always efficient, especially when the respondent group must have certain specialized or common characteristics. For example, it may be impractical to use random sampling among the general population for a study requiring prisoners because prisoners can likely be found relatively easily in a prison cell. A high dispersion of samples may induce higher costs for a researcher (Alexiades & Sheldon, 1996; Bernard, 2002; Snedecor 1939). The purposive sampling technique, also called judgment sampling, is the deliberate choice of an informant due to the qualities the informant possesses (Tongco, 2007). It is a nonrandom technique that does not need underlying theories or a set number of informants. The researcher decides what needs to be known and sets out to find people who can and are willing to provide the information by virtue of knowledge or experience (Bernard, 2002; Lewis & Sheppard, 2006). Despite its inherent bias, purposive sampling can provide reliable and robust data (Tongco, 2007).

The potential respondents for this study should ideally possess subject matter expertise and domain knowledge (by way of education, experience, or both) in Health Information Technology (HIT) in general, and Electronic Health Records (EHR) in particular. The requirement of such shared characteristics in the respondent group for this study makes purposive sampling the best suited sampling method for this study. Therefore purposive sampling was used to select the respondent group. The respondent profile used in this study consisted of Information Technology (IT) consultants, management consultants, project managers, physicians, nurses, healthcare facility administrators, and healthcare facility staff (such as pharmacists and physical therapists) who have been part of an *EHR experience* for a period of one year or more during the last five years. *EHR experience* is defined in this study as having been involved with the implementation, use, and maintenance of EHR during the stated period.

Table 2 shows the population to which the respondents belonged to. American Health Information Management Association (AHIMA) members register themselves across multiple forums. The number of distinct respondents with access to complete the survey was averaged across all AHIMA forums, resulting in a total of 5,646 eligible participants. Vidant Health Technology and Healthcare Information and Management Systems Society (HIMSS) were also part of the respondent population.

Table 2 Survey Respondent Population.

Organization-Association	Membership
AHIMA Care Coordination and Management Forum	510
AHIMA Clinical Documentation Improvement Forum	741
AHIMA Coding, Classification & Reimbursement Forum	8000
AHIMA Confidentiality, Privacy & Security Forum	3600
AHIMA Data Analytics Forum	438
AHIMA Health Information Technologies & Processes Forum	3700
AHIMA Healthcare Leadership and Innovation Forum	2400
AHIMA Long Term Post Acute Care (LTPAC) Forum	178
Vidant Health Technology Employees	200
HealthCare Information and Management Systems Society Chicago Chapter (HIMSS)	3000

Based on Cochran's (1977) sample size formula, Bartlett et al. (2001) provided minimum sample sizes to target for continuous and categorical data based on a given population size. Cochran's (1977) formula uses two factors: (a) the risk the researcher is willing to accept in the study, commonly called the margin of error, and (b) the alpha level which is the risk of finding a difference that does not actually exist in the sample. In general, an alpha level of 0.05 is acceptable for most research (Bartlett et al., 2001). For continuous data, a general rule of thumb is five percent margin of error (Bartlett et al., 2001). Bartlett et al. (2001) published the criteria for determining minimum sample size for a given population size for continuous data, using Cochran's formula. The population size for this study was 5,646. Based on the calculations suggested by Bartlett et al. (2001), the minimum required corresponding sample size using Cochran's formula is 119, for an alpha value of 0.05 and acceptable error rate of 3%.

Structural Equation Modeling (SEM) often requires a larger sample size than other statistical methods such as multiple regression (Kline, 2016). Wang and Wang (2012) stated that sample size determination is complicated and there is no one best method for determining sample size for each SEM scenario. Some factors influencing the sample size determination include the study design itself, number of manifest variables for each factor in the study, degree of multi-variate non-normality, complexity of the model, model estimator used and the number of missing data. Further, Wang and Wang (2012) proposed "10 cases/observation per indicator variable", a minimum of "5 cases/observation per free parameter" (p. 392) and a minimum of "10 times the number of free parameters" (p. 392). According to Wolf et al. (2013), sample size requirements for SEM studies commonly range between 30 and 460 participants. Schreiber et al. (2006) recommended a minimum of 10 participants per variable in order to maintain the stability of the parameter estimates. According to Hox and Bechger (1998) and Weston and Gore (2006), the recommended minimum sample size for SEM analysis is 200. Furthermore, Nunnally and Bernstein (1994) recommended 20-30 participants per independent variable within SEM studies in order to increase the chances that results may be replicated and not mere artifact.

This research study had 360 respondents (360 responded to the questionnaire survey). After data cleaning which involved elimination of incomplete/missing responses/cells, the useful data for analysis comprised of 316 responses, thus providing an acceptable sample size for this study based on the foregoing discussion.

Statistical power refers to the probability of finding a result given that the effect does exist in the population (Miles & Shevlin, 2001). In the context of SEM, at the model level, statistical power denotes the "sensitivity of $\chi 2$ to detect model misspecifications" (Brown, 2006, p. 413). Cohen (1988) prescribe a conventional cut-off value of 0.80 for acceptable statistical power. To determine the statistical power, the approach proposed by MacCallum et al. (1996) was used. It draws on non-central $\chi 2$ distributions and the root mean square error of approximation (RMSEA) statistics to test the null hypothesis that a model demonstrates a close fit in the population. To compute the power using this approach, the significance level (α), the RMSEA value below which the model is considered a reasonable fit (H_0), the RMSEA value above which the model is considered a bad fit (H_a), sample size (N), and the degrees of freedom (df) need to be specified. By setting α=0.05, H_0=0.05, H_a =0.08, N=316 and df identified from the theoretical model, the calculated value of power for the model used in this research study was greater than 0.90. This value exceeds the conventional cut-off value of 0.80 for acceptable statistical power prescribed by Cohen (1988).

Effect Size, p-value, Confidence Interval

Effect size is an objective and standardized measure of the magnitude of the observed effect (Field et al., 2012). Pearson's correlation coefficient *r* is a commonly used measure to report effect size (Field et al., 2012). The *p* value is the probability of obtaining a test statistic as large as, or larger than that obtained in the study by chance, if the null hypothesis were true. The null hypotheses is rejected in favor of the alternate hypothesis if the *p* value obtained is less than alpha, the predetermined level of statistical significance. If the obtained *p* value is greater than alpha, the null hypothesis is accepted (Rao, 2012). For this study, an alpha value of 0.05 was used.

Confidence interval (C.I.) is a range of values that are believed to contain, with a certain probability, the true value (i.e. the population's value) of a computed statistic for a sample of observations. A 95% C.I. is typically used in statistical research (Field et al., 2012), and therefore the same has also been used in this study.

Demographics

As previously stated, the survey had 360 respondents who met the respondent profile, of which 316 responses remained as useful responses for data analysis after the data cleaning process required before any statistical analyses. The demographic analysis was performed to understand the background of the survey respondents. About 66% respondents indicated that their most recent EHR experience was still in progress, while 27% and 6% respondents had completed their most recent EHR experience within the last one and two years respectively. The primary occupation of 43% of respondents was the medical profession, while that for 23% of the respondents was Information Technology. Among the respondents, 17% identified their profession to be project management, while 6% were business support/operations managers. Distribution of respondents by their job title (in their most recent EHR experience) is shown in Figure 2.

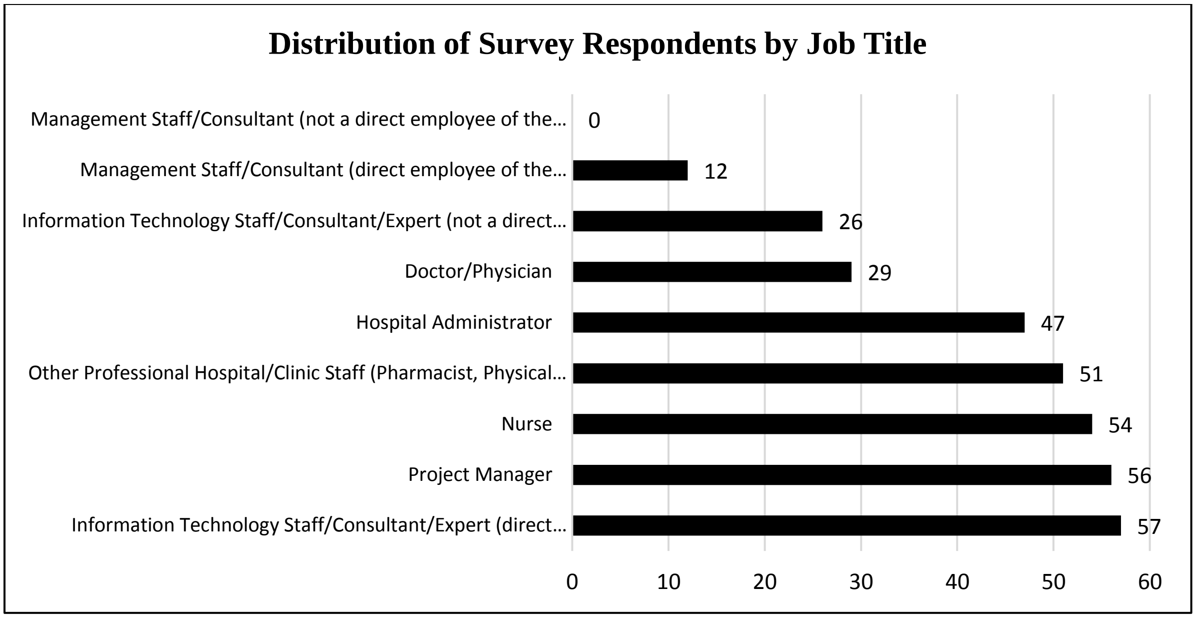

Figure 2. Distribution of Survey Respondents by Job Title.

Figure 3 shows the geographical distribution (distribution by region) of where the most recent EHR experience of the respondents took place. Nearly 30% of the respondents had their most recent EHR experience in the Southern region of the United States, 24% in the Western region of the United States, and 24% in the Midwest. Figure 4 shows the distribution of the type of organization where the most recent EHR experience of the respondents took place. With respect to the type of organization where their most recent EHR experience took place, 29% of respondents had their most recent EHR experience in a Single Hospital/Multi Hospital integrated delivery system, followed by 17% in an academic medical center (healthcare provider affiliated with a college or university). With respect to the organization where their most recent EHR experience took place, 46% of the respondents reported that the approximate total annual revenue in US dollars was between $500,000 and $2 Million. Over 24% of these organizations employed 850-1,000 full-time direct employees while just under 1% employed over 6,000. A total of 203 respondents indicated that the organization where their most recent EHR experience took place had employed consultants and contractors who worked on EHR implementation/maintenance/use. Of these respondents, 47% were unable to estimate the actual count of consultants/count, and 37% estimated this count to be 1-30.

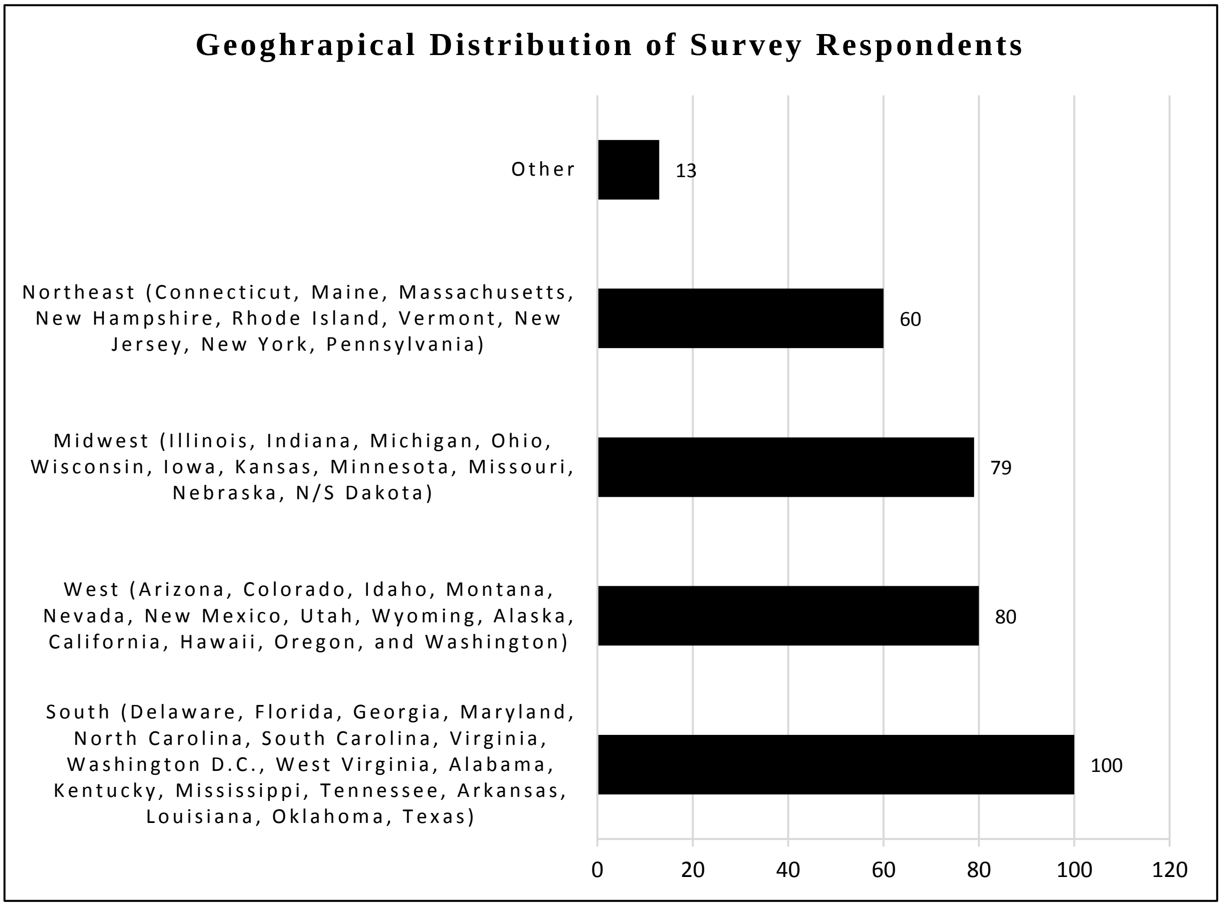

Figure 3. Geographical Distribution of Survey Respondents.

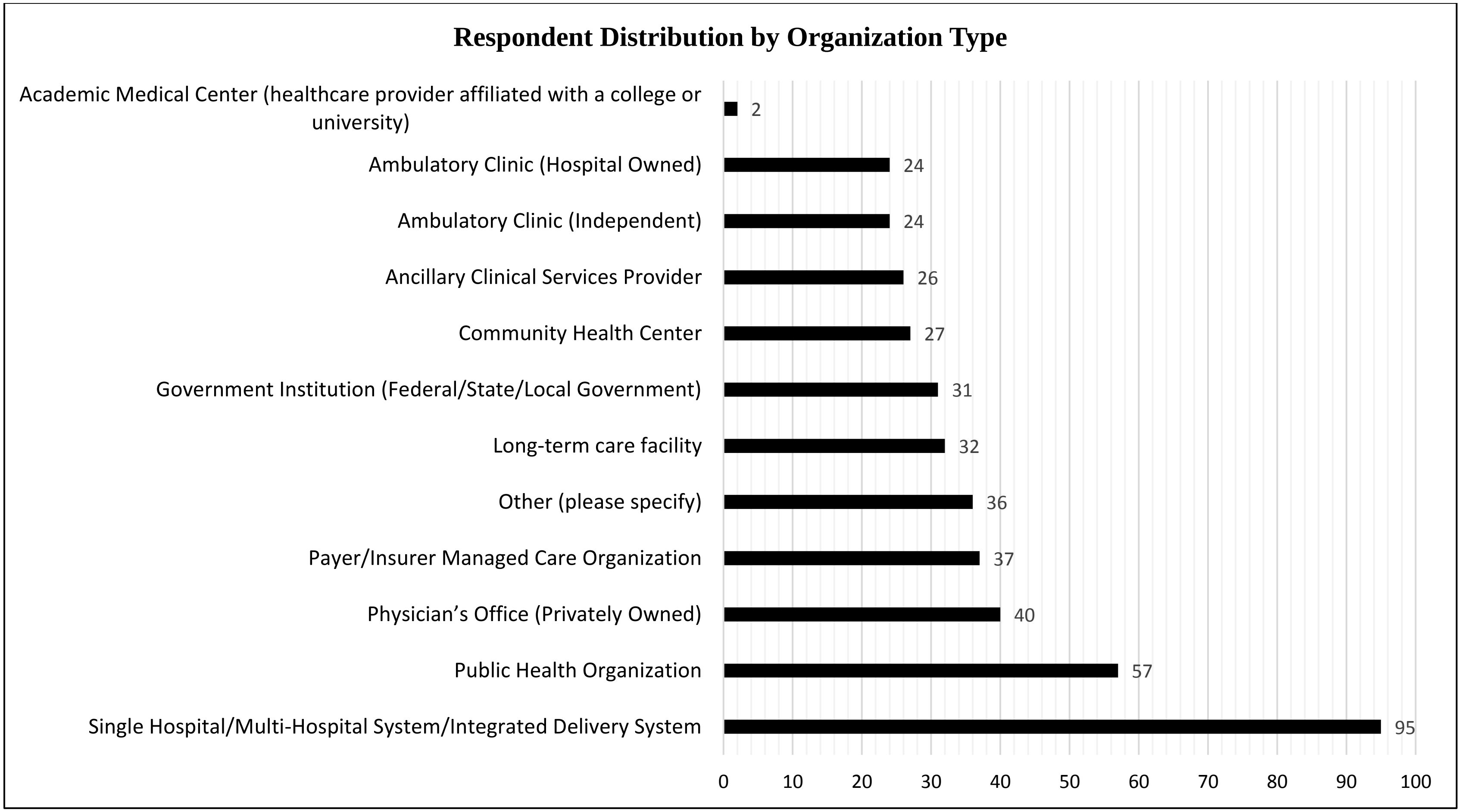

Figure 4. Respondent Distribution by Organization Type.

The survey respondents reported their affiliation with one or more professional societies which is shown in Figure 5. The top three affiliations were with AHIMA, HIMSS, and the American Medical Association (AMA).

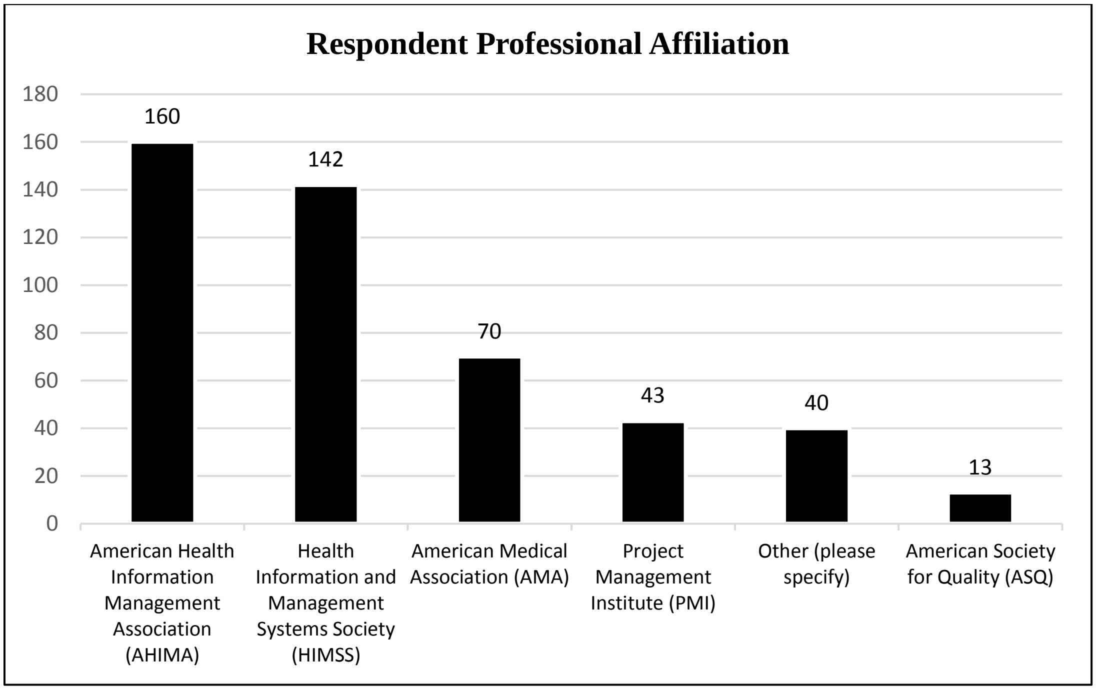

Figure 5. Respondent Professional Affiliation.

Statistical Analysis

This section details the statistical analysis conducted. First, the factorability results are presented, followed by reliability analysis. This is followed by structural equation modeling results and findings from hypotheses testing.

Factorability Results

Factorability relates to the appropriateness of conducting factor analysis on a collection of variables and is commonly verified by the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test) and Bartlett’s test of sphericity (Worthington & Whittaker, 2006).The Kaiser-Meyer-Olkin (KMO) test was used to validate sampling adequacy in this study. The

KMO test is measure of sampling adequacy (Kaiser, 1970) is a test that indicates how suitable the data is for factor analysis. Values greater than 0.9 are superb, between 0.8 and 0.9 are great, between 0.7 and 0.8 are good, between 0.5 and 0.7 are mediocre (Hutcheson & Sofroniou, 1999). For the data set under consideration in this study, the KMO value was calculated to be 0.98 thus confirming the sampling adequacy.

The first step to perform when conducting a factor analysis is to look at the correlations among variables for two potential problems (Field et al., 2012): (a) correlations that are not high enough, and, (b) correlations that are too high. Bartlett's test of Sphericity provides an assessment of whether the overall correlations are too small. Bartlett's test of Sphericity examines whether the correlation matrix would be an identity matrix (i.e.) every variable correlated very poorly with the other variables and hence the correlation coefficients are all zero (Field et al., 2012). A significance value of less than 0.05 on the Bartlett's test of Sphericity is required to conclude that the data collected is suitable to assess the central goal of the study (Bartlett, 1937; Williams et al., 2010). For the data set under consideration in this study, Bartlett's test of sphericity yielded $\chi 2$ (351) = 7,938, $p < 0.001$, thereby indicating that correlations between items was sufficiently large for factor analysis. The results of the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO test) and Bartlett's test of sphericity for the data set under consideration in this study indicate that the employment of factor analysis and SEM to the data set were appropriate.

However, Field et al. (2012) caution that a significant Bartlett's test does not necessarily mean that the correlations are high enough to make the analysis meaningful. Field et al. (2012) recommended identifying variables that have very low correlations (about 0.3) with several other variables and excluding them from subsequent factor analyses. Field et al. (2012) also state that "multicollinearity causes problems in factor analysis because it becomes impossible to determine the unique contributions to a factor of the variables that are highly correlated" (p. 771). In this regard, they recommend reviewing the correlation matrix for high correlations of greater than 0.8 and elimination of variables contributing to multicollinearity. In addition to implementing the above recommendations, an exploratory factor analysis (EFA) was also conducted in an effort to hone the variables. Based on all of the above actions, the items listed in Table 3 (below) were removed from subsequent analyses.

Table 3 Items Removed from Factor Analysis.

Items Removed	Rationale
t2, t4, t5, t6, t8, t9, t11, d40, d44	Variables loaded on more than one factor with a factor loading of 0.3 or more and/or correlation co-efficient with other variables measuring same construct is 0.3 or less
o12, o13, o16, s34, d43, d46, d47	Variables loaded on factors distinct from what they intended to measure, with a factor loading of 0.3 or more

Next, further checks for multicollinearity were performed to ensure lack of multicollinearity after removal of above items. Towards this end, the Variance Inflation Factor (VIF) and tolerance estimates were examined. VIF value exceeding 10 suggests severe multicollinearity (Freund, Wilson, & Sa, 2006; Hair et al., 1995; Kutner et al., 2005; Mason et al., 1989). VIF thresholds of 5 are common in research literature (De Jongh et al., 2015). In addition to this, the tolerance estimates for each variable must be greater than 0.20 to verify the absence of multicollinearity (Darlington, 1990). For the data set under consideration, VIF values obtained were under 5 and the tolerance ratio was greater than 0.20 thereby demonstrating the lack of multicollinearity.

Reliability Analysis

Reliability holds considerable importance for test construction for it provides the information as to the stability of test scores (Kline, 2005). Internal consistency reliability reflects the extent to which items within an instrument measure various aspects of the same characteristic or construct (Revicki, 2014). Reliability was calculated using Cronbach's Alpha, a common measure of test and scale reliability (Nunnally et al., 1967; Santos, 1999). Measurement of internal consistency reliability is of paramount importance in questionnaire survey research, with Cronbach's Alpha value of 0.70 and higher indicating acceptable reliability of the instrument (Field et al., 2012; Nunnally et al., 1967; Cronbach, 1951). The ease of use (EU) subscale consisted of 3 items ($\alpha = 0.75$), the organizational learning capability (OLC) subscale consisted of 3 items ($\alpha = 0.83$), the organizational absorptive capacity (ACAP) subscale consisted of 9 items ($\alpha = 0.96$). The service-dominant (SD) orientation subscale consisted of 11 items ($\alpha = 0.94$). The user attitudes (UA) subscale consisted of 3 items ($\alpha = 0.85$). The intention to use (IU) subscale consisted of 2 items ($\alpha = 0.9$). George and Mallery (2003) provide the following rules of thumb: "_ > .9 – Excellent, _ > .8 – Good, _ > .7 – Acceptable, _ > .6 – Questionable, _ > .5 – Poor, and _ < .5 – Unacceptable" (p. 231). Based on the calculated values, it is concluded that the survey instrument demonstrated acceptable to excellent reliability. Scales for performance expectancy (PE), result demonstrability (RD), and user satisfaction (USAT) had one item each after eliminating items presented in table 1. Table 4 and Table 5 report on the items used in the survey along with their factor loadings and α values.

Table 4 Independent Variables-Descriptive Statistics.

Independent Variables	Mean	Standard Deviation	Skewness	Kurtosis	Factor Loadings	R^2
Subscale EU α = 0.75						
t1. I find EHR to be user-friendly	4.41	0.72	-1.04	0.56	0.53	0.63
t3. It is possible to become skilled at using EHR	4.61	0.51	-0.73	-0.84	0.62	0.58
Subscale PE						
t7. Using EHR increases productivity	4.50	0.64	-1.00	0.20	0.40	1.00
Subscale RD						
t10. The results of using EHR are apparent to me	4.60	0.52	-0.69	-0.91	0.62	1.00
Subscale OLC α = 0.83						
o14. The organization looks for and acquires any necessary and/or specific knowledge it lacks from outside the organization	4.51	0.62	-1.02	0.75	0.76	0.69
o15. Formal and reiterative procedures are used to evaluate results	4.33	0.75	-0.85	0.00	0.40	0.54
o17. There is an atmosphere of trust and collaboration among the personnel of the organization leading to cooperation when an opportunity or problem that needs a solution arises	4.44	0.68	-1.11	1.13	0.80	0.63

Independent Variables	Mean	Standard Deviation	Skewness	Kurtosis	Factor Loadings	R^2
Subscale ACAP α = 0.96						
o18. The organization as a whole is successful in learning new things	4.45	0.68	-0.96	0.21	0.79	0.70
o19. The organization and its people are able to successfully acquire internal and external knowledge	4.48	0.64	-1.05	0.97	0.78	0.70
o20. There are routines to identify, value, and import new information and knowledge	4.47	0.65	-0.97	0.43	0.71	0.70
o21. There are adequate routines to analyze the information and knowledge obtained	4.43	0.68	-1.20	2.03	0.82	0.73
o22. There are adequate routines to assimilate new information and knowledge	4.44	0.69	-1.18	1.42	0.93	0.75
o23. The organization and its people are able to successfully integrate existing information into new knowledge	4.43	0.68	-0.95	0.38	0.86	0.71
o24. Existing information is transformed into new knowledge effectively	4.43	0.71	-1.09	0.76	0.89	0.77
o25. Internal and external information and knowledge are successfully exploited into concrete applications	4.43	0.70	-0.98	0.26	0.89	0.75
o26. Knowledge is effectively incorporated into new products or services	4.45	0.67	-1.01	0.57	0.78	0.73

Independent Variables	Mean	Standard Deviation	Skewness	Kurtosis	Factor Loadings	R^2
Subscale SD Orientation	α = 0.94					
s27. The organization leads in introducing radical product and service innovation	4.24	0.87	-1.00	0.54	0.52	0.46
s28. The organization constantly considers introducing new services that satisfy the healthcare receiver's needs	4.44	0.66	-0.88	0.25	0.60	0.63
s29. The organization's product and service development is based on good market and customer information	4.42	0.69	-1.01	0.62	0.68	0.66
s30. There is a good sense within the organization of how customers value the organization's products and services	4.46	0.67	-1.09	0.96	0.88	0.70
s31. The organization is healthcare receiver focused	4.60	0.55	-1.17	1.69	0.55	0.50
s32. The organization competes primarily on the basis of service differentiation	4.31	0.83	-0.80	-0.60	0.62	0.69
s33. The organization puts healthcare receiver's best interest first	4.60	0.57	-1.26	1.70	0.49	0.40
s35. Technical innovation is readily accepted	4.43	0.70	-1.32	2.34	0.83	0.64
s36. Management actively seeks innovative ideas	4.47	0.69	-1.39	2.59	0.77	0.65

Independent Variables	Mean	Standard Deviation	Skewness	Kurtosis	Factor Loadings	R^2
s37. Innovation is readily accepted in program/project management	4.50	0.60	-0.93	0.76	0.79	0.75
s38. People are not penalized for new ideas that don't work	4.46	0.64	-0.92	0.39	0.60	0.64

Note: N = 316

Table 5 Dependent Variable-Descriptive Statistics.

Dependent Variables	Mean	Standard Deviation	Skewness	Kurtosis	Factor Loadings	R^2
Subscale UA $\alpha = 0.85$						
d39. I believe that EHR is an appropriate tool to use to provide service to healthcare receivers	4.57	0.52	-0.55	-1.11	0.78	0.71
d41. I believe EHR is useful for patient care and management	4.64	0.51	-0.93	-0.40	0.79	0.52
d42. Using EHR is a wise idea	4.55	0.55	-0.71	-0.59	0.78	0.76
Subscale USAT						
d45. I am satisfied with the design and features of EHR	4.43	0.73	-1.15	0.81	0.81	1.00
Subscale IU $\alpha = 0.90$						
d48. I would use EHRs for a long time to come if am in a job where EHR use makes sense	4.59	0.51	-0.60	-1.15	0.58	0.84
d49. I predict I will use the EHR as long as I am given access	4.63	0.49	-0.62	-1.42	0.8	0.80

Note: N = 316

Structural Equation Modeling Results

The steps in performing SEM included: (a) specifying a model, (b) identifying a model, (c) estimating and evaluating the model, and (d) modifying and re-specifying the model. Results obtained from executing each of these steps are as follows.

Model Specification

The research model was developed a priori based on the extant literature review presented in chapter 2. The corresponding theoretical model is shown in Figure 1. Statistical analysis was performed using the SEM method. SEM was conducted using MLR estimation. The software used for the SEM analysis was R.

Model Identification

During the second step of SEM, the researcher determines if the model is over-identified, under-identified, or just-identified (Olobatuyi, 2006). The number of observations reflects "the number of variances and covariances among the observed variables" (Kline, 2005, p. 100) and "is equal to p(p+1)/2, where p is the number of observed variables" (Schumacker & Lomax, 2004, pp. 64-65). If the parameters to be estimated outnumber the available observations, the model is said to be under-identified, and if the parameters to be estimated turn out to be fewer than the observations, the model is said to be over-identified (Beran & Violato, 2010; Zhang, 2017). Based on the theoretical model specified, the number of parameters to be estimated were 75 and number of observations are 316, thereby confirming the model was over-identified.

Model Estimation and Evaluation

Of primary interest in SEM is the extent to which a hypothesized model "fits" or adequately describes the sample data set (Byrne, 2013). In general, model fit indices in SEM fall into one of the two categories: incremental fit indices (also termed as comparative fit indices) and absolute fit indices (Browne et al., 2002 Hu & Bentler, 1999). The comparative indices of fit measure the proportionate improvement in fit of a hypothesized model compared to a more restricted model, called the baseline model, while the absolute indices of fit assess the extent to which a model reproduces the sample data (Byrne, 2013; Hu & Bentler, 1999).

In this study, the model was estimated using the MLR method in SEM. The goodness-of-fit was measured with respect to multiple fit indices. Kline (2005) emphasized the need to draw on multiple fit indices rather than a single fit index due to the concern that each fit index might capture only a specific aspect of the model. The first of the statistics is the Chi-Square (χ^2) Test of Model Fit which is an absolute fit index (Gerbing & Anderson, 1992). Its value represents the discrepancy between the unrestricted sample covariance matrix and the restricted covariance matrix (Byrne, 2013). However, the χ^2 test has been criticized has been criticized for its tendency to reject models with large samples (Bentler & Bonett, 1980; Byrne, 2013). Scholars have proposed two alternate statistics to address this gap. Byrne (2013) states that to the extent that the χ^2 value of the hypothesized model is less than that of the baseline model, the hypothesized model is considered to exhibit an improvement of fit over the baseline model. For the data set under consideration in this study, the values of χ^2 for the hypothesized model was calculated to be 1219.5, and that of the baseline model was 10340.7 thereby supporting improvement of model fit over the baseline model. A second statistic that is commonly reported is the Chi-Square-to-degree-of-freedom ratio ($\chi2/df$). A value of < 5.0 is considered a good fit (Wheaton et al., 1977). For the data set under consideration in this study, the value for this ratio was calculated to be 2.5 thereby supporting a good fit.

Two additional model fit indices in the absolute fit category are root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR). The RMSEA takes into account the error of approximation in the population and asks the question "How well would the model, with unknown but optimally chosen parameter values, fit the population covariance matrix if it were available?" (Browne & Cudeck, 1993, pp. 137-138). This discrepancy, as measured by the RMSEA, is expressed per degree of freedom thus making it sensitive to the number of estimated parameters in the model. Values as high as 0.08 represent reasonable errors of approximation (Browne et al., 1993; Byrne, 2013; Kenny, 2015; Schumacker & Lomax, 2010; Wang & Wang, 2012). According to Steiger (1990), any value lower than 1.00 is assumed to be an adequate fit to the data, with values lower than 0.05 being a very good fit to the data.

The value of RMSEA obtained for the data set under consideration in this study was 0.07 with a 90% C.I. range of 0.06-0.07. This suggests that the model under consideration is sufficiently well fitting. The SRMR represents the average residual value derived from fitting of the variance-covariance matrix for the hypothesized model to the variance-covariance matrix of the sample data (Byrne, 2013). An SRMR value less than 0.08 is representative of a well-fitting model (Hu & Bentler, 1999; Wang and Wang, 2012). The hypothesized model in this study yielded an SRMR value of 0.05 indicating a good model fit.

The next set of fit indices that were examined were in the incremental fit category, the comparative fit index (CFI) and Tucker-Lewis Index (TLI) (Bentler, 1990; Tucker & Lewis, 1973). Both measure the proportionate improvement in model fit by comparing the hypothesized model in which structure is imposed with the less restricted baseline model (Byrne, 2013). A minimum value of 0.90 is considered representative of a well-fitting model (Kline, 2005; Wang and Wang, 2012). Schumacker and Lomax (2010) recommended TLI values close to 0.90

(preferably 0.95) for a good model fit with TLI values < 0.90 requiring the model to be re-specified. For the data set under consideration in this study, CFI was calculated to be 0.93 and TLI was 0.93 thereby demonstrating a good model fit. Table 6 summarizes the various fit indices for the overall model.

Table 6 Structural Equation Model Fit Indices.

Index	Value
χ^2 Baseline model	10340.7
χ^2 Hypothesized model	1219.5
df	486
p-value for χ^2 statistic	< 0.001
χ^2 / df ratio	2.50
RMSEA	0.07
C.I. of RMSEA*	0.06-0.07
SRMR	0.05
CFI	0.93
TLI	0.92

* 90% confidence interval of RMSEA

Parameter estimates of latent constructs depict the influence of a presumed causal construct on a presumed outcome construct (Garson, 2009; Kline, 2005). As Keith (1999) suggested, standardized parameter estimates or path coefficients with an absolute value below 0.05 do not suggest any meaningful influence, even when statistically significant. Absolute values of 0.05 and above are considered to have small but meaningful effects. Values with a magnitude of 0.10 and above are regarded as moderate, and those reaching 0.25 and above are viewed as large. Table 7 depicts the standardized parameter estimates and associated p-value in the overall model. By examining the values in the table, it can be concluded that the tested model demonstrated support for the theoretical relationships hypothesized in the overall model.

Table 7 Parameter Estimates for Model.

Construct	Standardized Parameter Estimate	Standard Error
RD	0.79*	0.07
EU	1.00*	0.08
PE	0.77 *	0.00
OLC	1.00*	0.07
ACAP	0.97*	0.00
SD Orientation	0.99*	0.09
Technology Factors	0.90*	0.00
Organizational Learning Factors	1.00*	0.11
Implementation Success	0.92*	0.08

Note: *Parameter estimate significant at p=0.05 level

Model Re-specification

The preceding section summarized the multiple fit indices and parameter estimates used to assess goodness-of-fit of the full latent variable model. Because the model was found to have an adequate fit on the basis of examining the collective statistical measures, additional re-specification of the model was not necessary.

Hypotheses Testing

The hypotheses for the current study (stated in chapter 2) were each tested individually for goodness-of-fit with the endogenous variable of the study. Results of the hypotheses testing are discussed below.

Hypothesis H1a: There will be a positive association between Ease of Use and Electronic Health Record implementation success.

Finding: Supported.

Explanation:

Using the model, EU was positive and statistically significant (1.02, *SE* = 0.08, Z = 12.85, p <0.05), supporting Hypothesis H1a. $\chi 2$ was 34.00, $\chi 2$/df ratio was 2.00. RMSEA was 0.06, with 90% CI being 0.03-0.08, SRMR was 0.02. CFI was 0.99, TLI was 0.99. Based on the above, it was concluded that hypothesis H1a was supported.

Hypothesis H1b: There will be a positive association between Result Demonstrability and Electronic Health Record implementation success.

Finding: Supported.

Explanation:

Using the model, RD was positive and statistically significant (0.80, *SE* = 0.05, Z = 12.82, p < 0.05), supporting Hypothesis H1b. $\chi 2$ was 5.61, $\chi 2$/df ratio was 0.43. RMSEA was 0.00, with 90% CI being 0.00-0.01, SRMR was 0.01. CFI was 1.00, TLI was 1.00. Based on the above, it was concluded that hypothesis H1b was supported.

Hypothesis H1c: There will be a positive association between Performance Expectancy and Electronic Health Record implementation success.

Finding: Supported.

Explanation:

Using the model, PE was positive and statistically significant (0.68, *SE* = 0.06, Z = 9.7 p < 0.05), supporting Hypothesis H1c. $\chi 2$ was 37.5, $\chi 2$/df ratio was 3.13. RMSEA was 0.08, with 90% CI being 0.05-0.11, SRMR was 0.03. CFI was 0.98, TLI was 0.97. Based on the above, it was concluded that H1c was supported.

<u>Hypothesis H2a:</u> There will be a positive association between Organizational Learning Capability and Electronic Health Record implementation success.

<u>Finding:</u> Supported.

<u>Explanation:</u>

Using the model, OLC was positive and statistically significant (0.86, *SE* = 0.09, Z =9.05, $p < 0.05$), supporting Hypothesis H2b. $\chi 2$ was 102.6, $\chi 2$/df ratio was 4.2. RMSEA was 0.10, with 90% CI being 0.08-0.12, SRMR was 0.05. CFI was 0.96, TLI was 0.94.

RMSEA being a function of $\chi 2$ statistic, is influenced by the sample size and model size (Moshagen, 2012; Shi et al., 2019; Shi et al., 2017). Shi et al. (2019) investigated the effect of number of observed variables (i.e.) model size on RMSEA, TFI, and CLI fit indices. Shi et al. (2019) examined the behaviors of population fit indices and their sample estimates by manipulating the number of observed variables. Shi et al.'s (2019) results showed that RMSEA fit index reacted differently to varying model size than the TLI, CFI indices.

Lai and Green (2016) argued that RMSEA and CFI can provide inconsistent evaluations of fit under certain conditions, and cautioned against drawing the incorrect conclusion of problems in model specification due to this reason. Lai and Green (2016) emphasized that the two indices are designed to evaluate fit from different perspectives and the meaning of "good fit" based on (arbitrary) cutoff values are not well understood in current literature. Lai and Green (2016) urged scholars to not automatically disregard the model because an index fails to meet a cutoff. Instead they encourage researchers to try to explain why the indices disagree, and the implications of disagreement.

Other scholars have also provided guidance on interpreting RMSEA fit index that accounts for values larger than 0.08. According to Cangur and Ercan (2015), an RMSEA value falling between the range of 0.08-0.10 is an indication of a fit which is neither good nor bad. Kenny (2011) presented the perspective that RMSEA fit index cutoffs applied to the population and it was possible for the population RMSEA value to be under a specified value (which would not be known), but the sample the RMSEA value could be greater than 0.10. Marsh, Hau, & Wen (2004) agreed that strictly adhering to recommended cutoff values can lead to instances of Type I error (the incorrect rejection of an acceptable model).

In this case, the TLI value of 0.94 and CFI value of 0.96 support a strong model fit (i.e.) they provide evidence for not having to re-specify the model. One of the greatest advantages of using RMSEA is the possibility for a confidence interval to be calculated around its value (MacCallum et al., 1996). The CI for RMSEA with a lower cut-off value of 0.08 indicates a good model fit. Consistent with the above discussion and based on the fit values obtained, the researcher chose not to re-specify the model. Under the circumstances, it was concluded that hypothesis H2a was supported.

Hypothesis H2b: There will be a positive association between an organization's Absorptive Capacity and Electronic Health Record implementation success.

Finding: Supported.

Explanation:

Using the model, ACAP was positive and statistically significant (0.87, $SE = 0.07$, Z = 10.76, $p < 0.05$), supporting Hypothesis H2a. $\chi 2$ was 256.31, $\chi 2/df$ ratio was 2.95.

RMSEA was .08, with 90% CI being 0.07-0.09, SRMR was 0.04. CFI was 0.96, TLI was 0.95. Based on the above, it was concluded that hypothesis H2b was supported.

Hypothesis H3: There will be a positive association between the Service-Dominant orientation of healthcare organizations implementing Electronic Health Records and Electronic Health Record implementation success.

Finding: Supported.

Explanation:

Using the model, SERV was positive and statistically significant (0.88, $SE = 0.10$, $Z = 9.80$, $p < 0.05$), supporting Hypothesis H3. $\chi 2$ was 329.34, $\chi 2$/df ratio was 2.84. RMSEA was 0.08, with 90% CI being 0.07-0.09, SRMR was 0.05 CFI was 0.95, TLI was 0.94. Based on the above, it was concluded that hypothesis H3 was supported.

Summary

This chapter discussed the results of the statistical analyses performed on the data collected through a questionnaire survey. The goal was to examine whether a unique combination of technology attributes, organizational learning attributes and service attributes predict EHR implementation success. Due to the presence of latent variables in the research model, SEM was used for the data analysis. SEM helped to determine the goodness-of-fit of the theoretical model. Data cleaning and various tests to assess the suitability of the data were performed. Analysis to address any multi-collinearity was performed. Extensive statistical analysis using SEM and MLR was performed using the statistical software R. It was concluded after performing the statistical analyses that the proposed model has a good fit based on the values of multiple fit indices. Next, each of the hypotheses presented in chapter 2 was validated and the hypotheses were found to be supported thus establishing that EU, RD, PE, OLC, ACAP, and SD orientation had a statistically significant impact on EHR implementation success. In the next chapter, the value of these findings in terms of their contributions to research literature as well as their significance to the industry practitioner will be discussed. Limitations of this study and suggestions for future research will also be presented in the next chapter.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Introduction

In this chapter, findings after the statistical analyses of data are discussed with respect to technology, organizational learning, and service dimensions. Implications of the findings, conclusions that can be drawn, and opportunities for further research in the future are examined.

Summary of Findings

As noted earlier, this study was guided by five research questions. To answer these research questions, the researcher conducted a quantitative study. The research model was developed on the basis of a thorough literature review and the following theories: unified theory of acceptance and use of technology (UTAUT), technology acceptance model (TAM), and the perceived characteristics of innovating (PCI) theoretical models, in addition to foundational theories in organizational learning and service-oriented delivery. Because of the presence of latent variables in the research model, the statistical technique structural equation modeling (SEM) was utilized for the statistical analyses. Table 8 summarizes the expected result (based on literature review and theoretical basis) and actual results from performing the statistical analysis. A discussion is presented about the results with respect to the research questions and corresponding hypotheses, and implications for academicians and practitioners.

Table 8 Summary of Expected and Actual Results.

Dimension	Factors	Expected Result	Actual Result
Technology	Ease of Use	Positive Relationship	Positive Relationship
Technology	Performance Expectancy	Positive Relationship	Positive Relationship
Technology	Result Demonstrability	Positive Relationship	Positive Relationship
Organizational Learning	Organizational Learning Capability	Positive Relationship	Positive Relationship
Organizational Learning	Organizational Absorptive Capacity	Positive Relationship	Positive Relationship
Service	Service-Dominant Orientation	Positive Relationship	Positive Relationship

Research Question One: Can EHR implementation success be predicted by a select combination of technology, organizational learning and service attributes?

This research question is an over-arching one. Technologies such as telemedicine, computerized provider order entry (CPOE), clinical decision support (CDS), Electronic Health Records (EHR) and mHealth are referred to as health information technology (HIT) innovations in research literature (Labrique et al., 2013; Serova & Guryeva, 2018). Holistic evaluation of HIT implementations requires the incorporation of socio-technical aspects and organizational aspects in the research model (Ash et al., 2012; Cresswell & Sheikh, 2014; Cresswell et al., 2012; Hameed et al., 2012; Hsiao et al., 2011). The primary aim of this study was to investigate the association between a carefully selected set of technology attributes, organizational learning attributes, and service attributes on the implementation success of a HIT innovation, namely electronic health record (EHR). Because of the promise offered by EHR to make healthcare efficient, cost-effective, and safe, and because of other benefits of EHR such as public health improvement, ability to use data analytics to find trends and develop interventions, and ability to use geographic information to target vulnerable health groups (Chennamsetty et al., 2015; Laranjo et al., 2016; Menachemi & Collum, 2011; Wu et al., 2016; Zlabek et al., 2011), it is imperative that EHR implementations succeed. This study found a SEM model fit when considering the selected factors leading to the conclusion that a combination of technology, organizational learning and service attributes does predict EHR implementation success.

The technology attributes/constructs considered in this study included ease of use (EU), performance expectancy (PE), and result demonstrability (RD). Likewise, the Organizational learning attributes/constructs included organizational learning capability (OLC) and organizational absorptive capacity (ACAP), and the degree of service-oriented delivery among healthcare service providers was measured using the construct service-dominant (SD) orientation. Using SEM, an assessment of the full latent variable model was conducted. A combination of SEM fit indices was examined which led to a convergent and significant finding. Results indicated a good model fit, implying that EU, PE, RD, OLC, ACAP, and SD orientation effectively predicted EHR implementation success with statistical significance ($p < 0.05$). This answers the research question by confirming that EHR implementation success can indeed be predicted by the select combination of technology, organizational learning and service attributes considered in this study.

Several scholars have previously argued that study of HIT implementation and delivery requires focus on the broader organizational and environmental contexts and processes (Westbrook et al., 2007). Disruptive technological advances in healthcare offer a unique opportunity to understand and evaluate the changing inter-relationships between technology and human/organizational factors, thereby requiring theoretical models to incorporate organizational, human (socio) and environmental factors (Creswell et al., 2012). This study proposed and empirically validated a research model to predict EHR implementation success consisting of a carefully chosen set of technology, organizational learning, and service attributes. By doing so, it made a significant contribution to extant research literature on HIT implementation success in general, and EHR implementation success in particular. For this reason, the findings of this study should be of interest to researchers, academicians and healthcare industry practitioners. The findings and the value added are discussed in detail in this chapter.

Technology Dimension

Research Question Two: Do ease of use, result demonstrability and performance expectancy impact EHR implementation success?

Three distinct hypotheses corresponding to this question were developed and tested.

Hypothesis H1a: There will be a positive association between Ease of Use and Electronic Health Record implementation success

Hypothesis H1b: There will be a positive association between Result Demonstrability and Electronic Health Record implementation success

Hypothesis H1c: There will be a positive association between Performance Expectancy and Electronic Health Record implementation success

Each of the above hypotheses was tested by examining the fit indices of distinct SEM models created to examine the relationships between EU, RD, PE and EHR implementation success. Results demonstrated positive association with statistical significance between each technology factor and EHR implementation success ($p < 0.05$).

Importance of the Technology Dimension Findings

The technology dimension findings are consistent with prior research literature where EU (Ketikidis et al., 2012; Strudwick & Hall, 2015; Vitari & Ologeanu-Taddei, 2018), PE (Bawack & Kamdjoug, 2018; Kim et al., 2015 ; Maillet et al., 2015; Venugopala et al., 2016), and RD (Gagnon et al., 2014; Tavares & Oliveira, 2016) have been found to significantly impact intent to use technology and technology implementation success.

This study differs from prior work in research literature in two distinct ways. Past studies in research literature have not considered the comprehensive impact of technology attributes, organizational learning attributes, and service attributes on EHR implementation which is a research gap addressed by this study. An essential contribution of this study has been to address the research gap by including technology factors along with a unique combination of factors (EU, RD, and PE) on EHR implementation success on the basis of the Unified Theory of Acceptance and Use of Technology (UTAUT), Technology Acceptance Model (TAM), and the Perceived Characteristics of Innovating (PCI) theoretical models.

Secondly, prior studies in this domain did not include Information Technology (IT) staff in the target respondent profile thereby failing to consider the perspectives/responses of the IT staff (and also thereby creating a research gap), whereas it is vital to include the perspectives/responses of the IT staff in a study of this nature based in part in the IT domain. In these times where IT is a part of every functional area of industry (including the healthcare industry), IT staff are found to be employed in hospitals, clinics and in other healthcare provider facilities. Technical maintainability and supportability of EHR systems are two prominent aspects which have a bearing on EHR implementation success, and IT staff (by the definition and nature of their work) are heavily involved in both. In addition, as stated earlier, HIT is, after all, an IT innovation and hence the views of IT staff assume importance when studying its successful implementation. For all of the above reasons, they are arguably one of the key stakeholders in HIT implementations, and it is necessary to take their views into account. In this study, the IT staff were very much included in the target respondent profile. A demographics analysis reveals that 23% of the survey respondents were IT staff. Thus, this study takes the views/responses of the IT staff into consideration in a study on EHR implementation while also addressing the research gaps discussed earlier.

For the healthcare industry practitioner, the results suggest that EHR should be easy to use. The more complex EHR is, the lesser will be its chances of adoption. In addition, the results obtained from using EHR should be visible to everyone in the organization (results demonstrability). If the implemented EHR does not help the user attain a gain in job performance and yields lesser or no gain relative to the previous system, end-users are less likely to adopt and use the EHR system.

Organizational Learning Dimension

Research Question Three: Does organizational learning capability impact EHR implementation success?

The following hypothesis was developed corresponding to this question and tested.

Hypothesis 2a: There will be a positive association between Organizational Learning Capability and Electronic Health Record implementation success

This hypothesis was tested by examining the fit indices of a distinct SEM model for relationship between organizational learning capability (OLC) and EHR implementation success.

Results demonstrated positive association between OLC and EHR implementation success with statistical significance ($p < 0.05$).

Research Question 4: Does organizational absorptive capacity impact EHR implementation success?

The following hypothesis was developed corresponding to this question and tested.

> *Hypothesis H2b: There will be a positive association between an organization's Absorptive Capacity and Electronic Health Record implementation success*

This hypothesis was tested by examining the fit indices of a distinct SEM model for relationship between ACAP and EHR implementation success. Results demonstrated positive association between ACAP and EHR implementation success with statistical significance ($p < 0.05$).

Importance of Organizational Learning Capability Findings

OLC is the managerial and organizational characteristic/element that facilitates the organizational learning process or encourages an organization to learn (Goh & Richards, 1997). Avgar, Litwin, and Pronovost (2012) argued that lack of OLC was an organizational barrier to HIT implementation and use. Based on this, they proposed a conceptual framework incorporating OLC at strategic, organizational and frontline levels, to serve as a road map for healthcare organizations in their journey from paper-based to electronic systems. Lee, Lin, Yang, Tsou, and Chang (2013) investigated the relationship between OLC and operating room nurses' acceptance of HIT in Taiwan, and found that OLC indirectly impacted nurses' behavioral intent to use HIT systems through the mediation of other factors such as PE, effort expectancy, and social influence in an operating room setting.

More recently, Motahhari Nejad (2018) investigated the role of OLC on the acceptance of information technology by nurses of teaching hospitals in Iran. Motahhari Nejad (2018) concluded that OLC can impact major determinants of intent to use HIT systems in the context of nurses HIT use in teaching hospitals. Aside from the above stated studies, there have been no studies in research literature wherein OLC's association with HIT acceptance and implementations have been modeled and empirically tested (Lee et al., 2013), due to which this study makes a meaningful contribution to research literature by proposing and empirically testing a research model involving the association between OLC and HIT implementation success (in this particular study, EHR implementation success). Also, a distinct aspect of this study was that the research model considered a combined and comprehensive impact of technological and service attributes along with OLC, the like of which has not been considered in prior research studies thereby creating a research gap. The research gap is addressed in this study.

Medical professionals whose job titles were hospital administrators, nurses, physicians, and physical therapists constituted 43% of this study's respondents. The relative diversity in the respondent profile of this study has strengthened the outcomes and increased their generalizability and value for academicians and practitioners. Based on a review of extant research literature, it can be stated that consideration of OLC's impact on EHR implementation is significant and relevant. To support OLC, healthcare organizations would be well-advised to invest time and money towards encouraging their HIT professionals/employees to acquire and enhance internal knowledge and external (outside the organization) knowledge, which in-turn should enable better/improved decision-making and lead to successful implementations of large-scale HIT (such as EHR) (Huber, 1991; Slater & Narver, 1995).

One way to enhance internal knowledge and acquire external (outside the organization) knowledge could be through active engagement with professional bodies (involved in healthcare improvement and healthcare projects) such as the American Health Information Management Association (AHIMA), the Healthcare Information and Management Systems Society (HIMSS), and the Project Management Institute (PMI). It is heartening to note in this context that nearly 83% of this study's respondents were members of the American Health Information Management Association (AHIMA), the Healthcare Information and Management Systems Society (HIMSS), the Project Management Institute (PMI) and other such professional societies. Spear (2004) stated that an alternate form of acquiring new information (through feedback) is to lead to an improved precision of feedback by including a systematic, controlled implementation of prior experience. It is reasonable to conclude from this that taking the time to formally educate the team on best practices and lessons-learned from prior HIT implementations will enable and strengthen OLC. The finding underscores the importance of cultivating employee trust and collaboration which can lead to better cooperation when needing to find solutions to problems of various complexities.

In research literature, OLC scholars have defined active memory as the storing and retrieval of information acquired through interactions in individual networks and social networks (Cross & Baird, 2000; Cross et al., 2005). Undertaking of training programs for employees contributes to the development of social networks (Sánchez et al., 2010). Making employees' abilities known to the broader organization (through social networks or otherwise) will contribute to more effective decision-making (Lewis, K., 2003). In the above manner, OLC is enhanced which then supports improved and effective decision-making which in-turn contributes to HIT implementation success (in this study, EHR implementation success). The support with statistical significance for hypothesis 2b affirms that organizational ACAP has an impact EHR implementation success, and also confirms the positive association between OLC and EHR implementation success. While doing so, it also addresses several research gaps (already presented above in this section) and thus makes a significant contribution to research literature and thereby is of interest to the academician and researcher.

Implementing a technology system such as EHR requires a significant amount of preparation and collaboration between medical and non-medical staff and significant effort. Every step of the implementation is a learning experience. The lessons learned in each step should help to avoid making mistakes and increase efficiencies in subsequent steps of the implementation. Therefore the OLC aspect should be taken very seriously by the healthcare industry practitioner.

Importance of Organizational Absorptive Capacity Findings

OLC is a set of micro-processes and interrelationships concerning learning at the individual, group and organizational levels (as discussed in the preceding section). By contrast, ACAP, which is based on the concept of dynamic capabilities (DC), is the ability to change routines and reconfigure routines to maintain competitive advantage (Vera et al., 2011). ACAP reflects the ability of an organization to respond to *strategic* change by reconstructing its core capabilities (Teece et al., 1997; Wang & Ahmed, 2003). Kash et al. (2014) proposed a conceptual framework encompassing three dimensions (leadership, culture, and organizational technologies) relevant to transformative change, for measuring ACAP in healthcare organizations. Kash et al. (2014) argued that EHR itself was a transformative technology having far reaching impacts on organizational work processes in the delivery of healthcare. Wu, Wang, Song, and Byrd (2015) proposed a conceptual model to explain the importance of knowledge derived from *learning-about* EHR technology (i.e. pre-adoption learning activity) and to investigate ACAP's role in this process. Wu et al. (2015) posited that ACAP moderates the effect of knowledge from the *learning-about* phase on the outcomes of HIT adoption.

A prior study that attempted to investigate the impact of ACAP on HIT implementations was by Do Carmo Caccia-Bava, Guimaraes, and Harrington (2006), who proposed a measure of ACAP (that included managerial IT knowledge and communication channels) and tested its relationship to the level of success attained in implementing new (technology) systems. HIT implementation success was measured through cost, reliability, improved response, competitive advantage, user satisfaction and ease of use. However, the study had several limitations which could impact its generalizability. The respondents were limited to hospital administrators with the titles Chief Executive Officer, Chief Financial Officer, Chief Operating Officer, Controllers and Group Manager. The sampling was done at just 192 hospitals in the United States. Their study considered did not focus on any particular HIT system (such as EHR) and instead focused on HIT in general. Each HIT (e.g., EMR/EHR, telemedicine, hedonic healthcare websites) has some characteristics typical to it and brings with it a set of unique challenges with respect to its implementation. Therefore, it is likely that not all findings that apply to HIT implementations in general will apply to each specific HIT implementation. Lastly, do Carmo Caccia-Bava, Guimaraes, and Harrington's study (2006) sought to measure the sole impact of ACAP without considering other factors that might play a role in HIT implementation success.

In summary, there are very few prior studies in research literature which have considered ACAP in healthcare organizations, and these studies have many limitations that restrict the generalizability of results. This, by itself, is a research gap. Another research gap lies in the fact that no prior study has considered OLC and ACAP in a single grouping as the principal facets of the learning dimension. This study addresses the research gaps. Firstly, it has taken into account the limitations of prior studies and addressed them. Secondly, it has considered OLC and ACAP in a single grouping as the significant facets of the learning dimension. Thirdly, it adds a research study to an area of research literature (consideration of OLC and ACAP in healthcare organizational settings using an empirical research format) where very few prior studies exist to begin with. Thus, this study fills various research gaps and makes a significant contribution to research literature in the above ways, and should therefore be of interest to the academicians and researchers.

The results of this study have value for the practitioner as well. Knowledge acquisition capacity is related to an organization's ability to identify and acquire externally generated knowledge which may be important to its operations (Zahra & George, 2002). In the HIT context, healthcare organizations should actively enable opportunities for employees to enhance both breadth and depth of knowledge derived from external entities. Some examples include collaboration with universities, research institutes, governments, customers, and suppliers to obtain external information and knowledge (Xie et al., 2018). Knowledge assimilation capacity refers to a firm's routines and processes that allow the firm to analyze, interpret, and understand information obtained from external sources (Zahra & George, 2002). Healthcare leaders in industry could foster an environment encouraging productive debates involving industry benchmarks and lessons to be learned with respect to industry best practices. The above measures would enable the organization's own employees to become *outside-the-box* thinkers and come up with innovative solutions when faced with challenges and issues with respect to EHR implementation, maintenance and use, thereby ultimately leading to EHR implementation success. Such a thought process would undoubtedly help the healthcare organization to become and remain an industry leader once the EHR implementation has been successfully completed as well. Last but not least, assimilating external knowledge and best practices may improve efficiencies, help avoid repetitive work, and update the organization's knowledge reserves (Atuahene-Gima, 2003).

Knowledge transformation denotes an organization's ability to develop and refine the routines that facilitate the combining of existing knowledge and newly acquired/assimilated knowledge (Zahra & George, 2002). This can be accomplished by creating an atmosphere of continuous learning, and fostering the ability to obtain, understand, and integrate external knowledge (Xie et al., 2018). For example, a HIT Innovation Lab could be established in a healthcare organization which specializes in integrating external and internal knowledge to innovate and continuously improve. Such a lab would, for example, strive to obtain forward-thinking knowledge from external entities, and develop *proof-of-concept* or *proof-of-technology* HIT prototypes which would be tested and deployed in a phased manner. Such learning and experience would serve the dual goals of innovating and continuously improving, while also enabling the absorption and use of the knowledge and experience to ensure the success of HIT implementations.

Knowledge exploitation capacity is related to the ability of organizations to incorporate and utilize the acquired, assimilated, and transformed knowledge into their operations and routines to solve real-world problems, allowing them to create new operations, competencies, and routines (Camisón & Forés, 2010; Mitchell, 2006). Therefore, exploitation of the absorbed knowledge should lead to more and greater successes pertaining to the implementation and use of HIT systems, which in-turn should lead to higher return-on-investment along with cost savings and increased efficiencies over the long run.

Service Dimension

Research Question Five: Does a service-dominant orientation impact EHR implementation success?

The following hypothesis was developed corresponding to this question and tested.

Hypothesis H3: There will be a positive association between the Service-Dominant orientation of healthcare organizations implementing Electronic Health Records and Electronic Health Record implementation success

This hypothesis was tested by examining the fit indices of a distinct SEM model for relationship between SD orientation and EHR implementation success. Results demonstrated a positive association between SD orientation and EHR implementation success with statistical significance ($p < 0.05$).

Importance of Service Dimension Findings

In the context of this study, *service* is defined as the application of specialized competencies (i.e. knowledge and skills) through deeds, processes, and performances for the benefit of another entity or the primary entity itself (Vargo & Lusch, 2004). A central implication of SD orientation is the notion of *value co-creation* where organizations, customers and other actors co-create value through their service interactions with one another. SD orientation is defined as a co-creation capability, resulting from a firm's individuated, relational, ethical, empowered, developmental, and concerted interaction capabilities. (Karpen et al., 2012). Porter and Lee (2013) argued that healthcare systems around the world have been struggling with rising costs and uneven quality despite well-intentioned clinicians. To solve this problem, they advocated a fundamentally new strategy for delivering healthcare, one at whose was maximizing value for the patients through the creation of a value-enhanced IT platform for patients.

Empirical research studies involving value co-creation are sparse in research literature. The concept of SD orientation applied to healthcare is relatively new (Joiner & Lusch, 2016), and prior studies involving the application of value co-creation in healthcare are of a conceptual nature only (Hardyman et al., 2015). This is a research gap. Additionally, no prior study in research literature has considered a comprehensive and unique combination of technology factors, learning domain factors, and service orientation in the context of either healthcare operations or HIT implementations, causing another research gap. This study has addressed both research gaps by incorporating the service dimension in a HIT (EHR implementation) study, and additionally incorporating a comprehensive and unique combination of technology factors, learning domain factors, and service orientation in the context of HIT implementations. In addition, the finding of this study of a model fit with the considered factor combination and the positive association between the SD orientation of healthcare organizations implementing EHRs and EHR implementation success is an addition to research literature which should be of interest to academicians and researchers.

For the practitioner, this finding offers several preliminary insights of value. At the heart of SD orientation is an organization’s capability to collaborate both internally and externally to produce value. In the context of EHR implementations, partnering and closely collaborating with EHR vendors could help create innovative services to satisfy the healthcare receiver’s needs. Taking this a step further, collaborating with patients directly to better understand their needs and priorities with respect to digitization of health records is likely to contribute to service innovation, which in-turn would help with EHR implementation success. Internal collaboration could be facilitated by implementing mechanisms for employees to share knowledge (e.g., a HIT Innovation Lab, as previously discussed in this work). As part of the service orientation, the healthcare receivers (patients) could also be invited to provide their inputs regarding EHR and its' implementation. Such an action would be a positive reflection of the organization's culture with respect to its service focus (in this instance, providing service not only to internal users, but to the external users viz. the patients as well), as well as demonstrate its commitment to encouraging value co-creation at multiple organizational levels. A logical next step would perhaps be to create reward and recognition systems that incentivize such positive behaviors, which would have an iterative effect on the service orientation aspect. Thus, healthcare organizations that subscribe to the SD orientation would view EHR implementation as an enabler of excellent end-to-end patient centered service-experiences. Such actions and mindset would contribute directly and indirectly to EHR implementation success besides preparing the healthcare organization to be an industry leader that has performance excellence and excellent customer service. Figure 6 summarizes findings discussed in this section

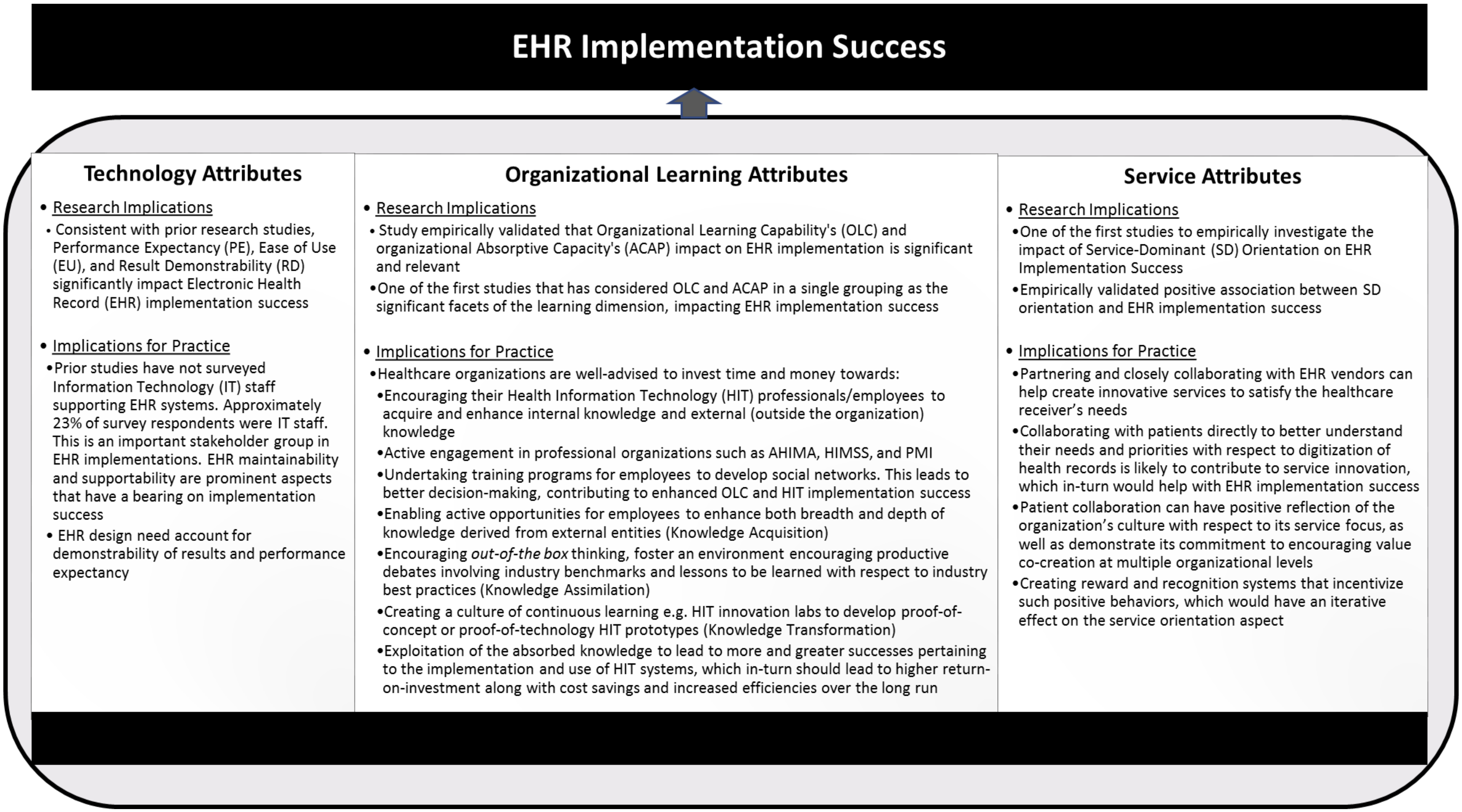

Figure 6. Summary of Findings.

Limitations of the Study

This research has generated newer insights pertaining to EHR implementation success. Nonetheless, given the inherent complexity of developing and testing a research model with survey data and measuring latent factors influencing HIT implementations, studies such as this are likely to have limitations. The availability of certain resources and not others, the cost of conducting research work, and the time available to conduct research work sometimes dictate the way the data can be practically collected and analyzed, and this process contributes to the limitations of every research study. Admittedly, this research study too has some limitations.

It is difficult in practice to collect survey data directly from healthcare provider organizations in the United States. The reasons for this are varied and complex. Some of the reasons include the lack of desire of healthcare providing organizations to deal with student researchers (in the United States, very strict laws apply to the healthcare field and healthcare is strictly regulated, and hence healthcare providers may fear law suits resulting from exposure of healthcare data and information), lack of willingness on the part of individuals and healthcare organizations to share data/information, the busy schedules of everyone working at healthcare provider facilities and hence their reluctance to give some of their time to student researchers, culture and business environment influences (United States has more of Hofstede's individualistic culture orientation (2009) and a very competitive business world which includes competition between healthcare providers). A majority of the data collection was therefore done by reaching out to the membership of massive healthcare professional societies such as AHIMA and HIMSS whose members are a part of healthcare provider organizations, and administering the survey instrument to those respondents that met the required respondent profile. Nearly 83%

of the survey respondents for this study were affiliated with one or more professional organizations such as AHIMA, and HIMSS. This is a limitation in the sense that had the source of data or the sampling plan been different, it is possible that the results would have been different even when using the same target respondent profile.

A second limitation is the reported annual revenue of healthcare organization where EHR was implemented. Approximately 22% of respondents reported the annual revenue of the location where the EHR implementation/use/maintenance was taking place to be between $2 Million and $4 Million. This corresponds to medium to large healthcare provider facilities in the United States. In addition, 29% of respondents indicated the organization where EHR was implemented was at a single-hospital/multi-hospital/integrated delivery system. Again, this too corresponds to medium to large healthcare provider facilities in the United States. Medium to large healthcare providers in the United States are likely to have robust and mature organizational learning routines in place. Employees at these organizations may have more resources at their disposal to engage in knowledge acquisition, assimilation, transformation and exploitation – the four key aspects of ACAP, than staff at relatively smaller healthcare organizations. This and other similar trends in demographics of the survey respondents may have influenced the results of the study which could be considered a limitation. A follow-up study could consider the same data set obtained in this study and group the survey results by the size and type of healthcare organization and redo the data analysis to arrive at results that have been moderated by provider organization type and size.

This study was conducted in the United States and all of the study's respondents were based in the United States, whose gross domestic product (GDP) spending ranks highest in healthcare spending among developed nations of the world ("US Health Care Spending Highest

Among Developed Countries", 2019). According to data released by the Organization for Economic Co-operations and Development (OECD), the health spending in the United States was estimated in 2018 at $10,586 per capita ("Health expenditure per capita", 2019). This statistic is vastly different from that of other developed nations in the OECD report (for example, Canada, whose corresponding spend was $4,974 per capita). The healthcare consumer in the United States therefore pays more for healthcare than do healthcare consumers in other countries with a different scale and format of the healthcare industry. Due to this, the expectations of United States healthcare consumers for factors such as the service component may be different from that of the healthcare consumer in other countries. For example, the service expectation in the United States may be much higher than that in other countries. This influence is a limitation of sorts.

This study focused on identifying technology, organizational learning, and service attributes impacting EHR implementation success. However, EHR is one among several HIT platforms. Technologies such as telemedicine, CPOE, and mHealth are also referred to as HIT innovations in research literature (Labrique et al., 2013; Serova & Guryeva, 2018). Each of these systems has unique barriers and implementation characteristics that were not considered in this study. Applying the findings from this study to all HIT implementations rather than just to EHR implementations may result in over-generalizing. Therefore, this could be considered a limitation as well.

EHR software are supplied by various vendors in the United States and around the world. Sone of these vendors include Epic Systems, NextGen Healthcare, Praxis, AmazingCharts EHR, Fusion, and Cerner. Though all of these EHR software comply with government mandated and legal guidelines for EHR, the user interface and programming structure for each of these is a little different. Such differences may have an impact on the technology constructs performance expectancy and ease of use. This research study focused on the EHR system/technology as a whole and did not consider variations in individual EHR software. Though this is a limitation of sorts, it is not a significant limitation because the software interface variations may at best impact the constructs PE and EOU, but would have no impact on the other constructs used in the study.

Suggestions for Future Work

The support found in this study for SD orientation and its association with EHR implementation success opens avenues for further/future research. As already stated, no prior study in research literature has considered a comprehensive and unique combination of technology factors, learning domain factors, and service orientation in the context of either healthcare operations or HIT implementations, the concept of SD orientation applied to healthcare is relatively new (Joiner & Lusch, 2016), and prior studies involving the application of value co-creation in healthcare are of a conceptual nature only (Hardyman et al., 2015). Future work could incorporate a different set of factors along with SD orientation into a research model designed using the HIT implementation context. This may provide for a more holistic view of antecedents to EHR implementation success. Such future work may help to lay a foundation on which to build multiple streams of research that investigate the combined and moderating effects of SD orientation and other factors of interest in HIT implementations.

This study was focused on EHR implementation success among healthcare providers in the United States. Future work could replicate this study in the healthcare environments of other countries and cultures. While doing so, it may be interesting to also include Hofstede’s (2009) cultural dimensions to the research model in order to study the influence of culture on the results.

Future work could address the limitations stated for this study and re-do it. For instance, data could be collected directly from one or more healthcare providers. Similarly, data collection could be from smaller healthcare provider organizations in the United States and elsewhere in the world to study the moderating impact of organizational size. Finally, applying this research model to examine other HIT technologies such as Telemedicine and mobile-Health could make beneficial contributions to both academic research as well as add to practitioner knowledge.

Conclusion

This dissertation modeled, tested and studied the relationships among a select set of technology, organizational learning, service attributes, and EHR implementation success. EHR is a vital part of HIT and HIT implementations are crucial because of their promise of heralding an efficient, effective, safe, cost-effective and evidence-based healthcare system in the United States and around the world. For this reason, the implementation success of HIT systems and EHR is very valuable. Prior studies pertaining to the implementation success of HIT systems and EHR were not as comprehensive as this study, in the sense that they did not consider the essential constructs pertaining to technology, organizational learning and service attributes which this study did. Additionally, this study addressed several research gaps in research literature which have been discussed in detail throughout the dissertation. In addition, it is the first study to test the role of SD along with other pertinent factors/constructs in a healthcare context and for a HIT implementation at that.

The importance of the study and its scope were discussed in chapter 1 of this dissertation. An extant literature review conducted in chapter 2 identified a paucity of research investigating this unique combination of attributes on EHR implementation success. An empirical validation of this model was conducted using the research methodology outlined in chapter 3. Chapter 4 detailed the results of this investigation which identified support for the hypothesis presented in chapter 2. Furthermore, it lent support to SEM procedures as a powerful statistical approach for testing the model. Chapter 5 delved into a discussion of findings, implications for researchers and practitioners, as well as limitations and avenues for future research. The value of the findings for academicians/researchers and healthcare industry practitioners has been elaborately presented in this dissertation.

The findings point to the value in taking into consideration technology, organizational learning, as well as service factors when studying HIT/EHR implementations. This should make sense because though the business world is technology driven today, organizational dynamics, people, and the accrual of service/benefits do contribute in no less measure to the successful implementation, maintenance and continued use of technology. Therefore, taking into consideration only one of these factors while ignoring others would be a serious mistake. In the world of intense competition that we live in today, constant innovation is absolutely necessary for long-term success, and OLC and organizational ACAP are essential ingredients for achieving such innovation. Technology by itself is not a panacea, but when used with the over-arching goal of providing excellent service to the members of the public and when continuously improved to keep pace with changing times through innovation, OLC, organizational ACAP, and SD orientation, HIT can do marvels for assuring the health and welfare of the citizens of the world.

REFERENCES

Abbett, S. K., Bates, D. W., & Kachalia, A. (2011). The meaningful use regulations ininformation technology: what do they mean for quality improvement in hospitals?. *Joint Commission journal on quality and patient safety*, *37*(7), 333-336.

Abelson, R., & Creswell, J. (2015). Data breach at anthem may forecast a trend. *New YorkTimes*. Retrieved from http://www.nytimes.com/2015/02/07/business/data-breach-atanthem-may-lead-to-others.html

About GIC HIMSS Chapter. (n.d.). Retrieved from http://greaterillinois.himsschapter.org/about-gic-himss-chapter

About HIMSS. (n.d.). Retrieved from https://www.himss.org/who-we-are

About the AHRQ Health Care Innovations Exchange. (n.d.). Retrieved from https://innovations.ahrq.gov/about-us

Adler-Milstein, J., & Jha, A. K. (2017). HITECH Act drove large gains in hospital electronichealth record adoption. *Health Affairs, 36*(8), 1416-1422.

Afnan, A., & Chandrasekaran, R. (2015). Factors Associated with EHR User Satisfaction in Small Clinic Settings.

Agha, L. (2014). The effects of health information technology on the costs and quality of medical care. *Journal of health economics*, *34*, 19-30.

Agrawal, A. (2002). Return on investment analysis for a computer-based patient record in the outpatient clinic setting. *Journal of the Association for Academic Minority Physicians:the official publication of the Association for Academic Minority Physicians*, 13(3), 61-65.

AHIMA Who We Are. (2019). Retrieved from http://www.ahima.org/about/aboutahima?tabid=story

Ahrens, W., & Pigeot, I. (Eds.). (2014). *Handbook of epidemiology* (Vol. 451). New York, NY: Springer.

Aiman-Smith, L., & Green, S. G. (2002). Implementing new manufacturing technology: Therelated effects of technology characteristics and user learning activities. *Academy of Management Journal*, *45*(2), 421-430.

Al-Adwan A.S., & Berger H. (2015). Exploring physicians' behavioural intention toward the adoption of electronic healthrecords: an empirical study from Jordan. *Int J Healthc Technol Manag. 15*(2):89–111.

Aldosari, B. M. B. (2004). Factors affecting physicians' attitudes about the medical information system usage and acceptance through the mandated implementation of integrated medical information system at the Saudi Arabia National Guard Health System: A modified technology acceptance model.

Alexiades, M. N., & Sheldon, J. W. (1996). Selected guidelines for ethnobotanical research: a field manual (No. Sirsi) i9780893274047).

Ali, M., Zhou, L., Miller, L., & Ieromonachou, P. (2016). User resistance in IT: A literature review. *International Journal of Information Management*, *36*(1), 35-43.

Alias, E. S., Mukhtar, M., & Jenal, R. (2018). Adoption of unified communications and collaboration from the perspective of diffusion of innovation and service-dominant logic: A preliminary view. *International Journal on Advanced Science, Engineering and Information Technology*, *8*(5), 1882-1889.

AlJarullah, A., Crowder, R., Wald, M., & Wills, G. (2018). Factors Affecting the Adoption of EHRs by Primary Healthcare Physicians in the Kingdom of Saudi Arabia: An Integrated Theoretical Framework. *International Journal of e-Healthcare Information Systems*, *5*(1), 126-138.

Alter, S. (2008). Defining information systems as work systems: implications for the IS field. *European Journal of Information Systems*, *17*(5), 448-469.

Ambrosini, V., & Bowman, C. (2009). What are dynamic capabilities and are they a useful construct in strategic management?. *International journal of management reviews*, *11*(1), 29-49.

Amoako-Gyampah, K., & Salam, A. F. (2004). An extension of the technology acceptance model in an ERP implementation environment. *Information & management*, *41*(6), 731-745.

Anderson, J. G. (2002). Evaluation in health informatics: Social network analysis. Computers in Biology and Medicine, 32, 179-193.

Ash, J. S., Berg, M., & Coiera, E. (2004). Some unintended consequences of information technology in health care: the nature of patient care information system-related errors. *Journal of the American Medical Informatics Association*, 11(2), 104-112.

Ash, J. S., Sittig, D. F., Guappone, K. P., Dykstra, R. H., Richardson, J., Wright, A., ... & Middleton, B. (2012). Recommended practices for computerized clinical decision support and knowledge management in community settings: a qualitative study. *BMC medical informatics and decision making*, *12*(1), 6.

Atkinson, N. L. (2007). Developing a questionnaire to measure perceived attributes of eHealth innovations. *American Journal of Health Behavior*, *31*(6), 612-621.

Atuahene-Gima, K. (2003). The effects of centrifugal and centripetal forces on product development speed and quality: How does problem solving matter? *Academy of Management Journal*, 46(3), 359–373.

Avgar, A. C., Litwin, A. S., & Pronovost, P. J. (2012). Drivers and barriers in health IT adoption. *Applied clinical informatics*, 3(04), 488-500.

Baker, A. (2001). Crossing the quality chasm: a new health system for the 21st century. *BMJ*, *323*(7322), 1192.

Baldwin, C. Y., & Clark, K. B. (1997). Managing in an age of modularity. *Harvard business review*, *75*(5), 84.

Bamberger, P. (2008). Beyond Contextualization: Using Context Theories to Narrow the Macro-Micro Gap in Management Research. *Academy of Management Journal*, 51(5), 839-846.

Banker, R. D., Bardhan, I. R., Chang, H., & Lin, S. (2006). Plant information systems, manufacturing capabilities, and plant performance. *MIS quarterly*, 315-337.

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ, 1986*.

Barki, H., & Hartwick, J. (1994). User Participation, Conflict, and Conflict Resolution: The Mediating Roles of Influence. *Information Systems Research*, 5(4), 422-438.

Bartlett, M. S. (1937). Properties of sufficiency and statistical tests. *Proceedings of the Royal Society of London. Series A, Mathematical and Physical Sciences*, 268-282.

Bartlett, K., & Kotrlik, J. (2001). Higgins,(2001). Organizational Research: Determining Appropriate Sample Size in Survey Research. *Information technology, learning, and performance journal*, *19*(1), 43-50.

Bates, D. W. (2005). Physicians and ambulatory electronic health records. *Health Affairs*, 24(5), 1180-1189.

Bates, D. W., Kuperman, G. J., Rittenberg, E., Teich, J. M., Fiskio, J., Ma'luf, N., ... & Komaroff, A. L. (1999). A randomized trial of a computer-based intervention to reduce utilization of redundant laboratory tests. *The American journal of medicine*, 106(2), 144-150.

Bates, D. W., Leape, L. L., Cullen, D. J., Laird, N., Petersen, L. A., Teich, J. M., ... & Vander Vliet, M. (1998). Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. *Jama*, 280(15), 1311-1316.

Bates, D. W., Teich, J. M., Lee, J., Seger, D., Kuperman, G. J., Ma'Luf, N., ... & Leape, L. (1999). The impact of computerized physician order entry on medication error prevention. *Journal of the American Medical Informatics Association*, 6(4), 313-321.

Bawack, R. E., & Kamdjoug, J. R. K. (2018). Adequacy of UTAUT in clinician adoption of health information systems in developing countries: The case of Cameroon. *International journal of medical informatics*, *109*, 15-22.

Bell, B., & Thornton, K. (2011). From promise to reality: achieving the value of an EHR: realizing the benefits of an EHR requires specific steps to establish goals, involve physicians and other key stakeholders, improve processes, and manage organizational change. *Healthcare Financial Management,* 65(2), 51-57.

Bentler, P.M., & Bonet, D.G. (1980). Significance tests and goodness-of-fit in the analysis of covariance structures. *Psychological Bulletin*, 88, 588–606.

Bentler, P. M. (1995). *EQS structural equations program manual*. Encino, CA: Multivariate Software.

Beran, T. N., & Violato, C. (2010). Structural equation modeling in medical research: a primer. *BMC research notes*, 3(1), 267.

Bernard, H.R. (2002). Research Methods in Anthropology: Qualitative and quantitative methods. 3rd edition. AltaMira Press, Walnut Creek, California.

Bharadwaj, A. S., Bharadwaj, S. G., & Konsynski, B. R. (1999). Information technology effects on firm performance as measured by Tobin's q. *Management science*, *45*(7), 1008-1024.

Bhattacherjee, A., Hikmet, N., Menachemi, N., Kayhan, V. O., & Brooks, R. G. (2006). The differential performance effects of healthcare information technology adoption. *Information Systems Management*, *24*(1), 5-14.

Black, S. E., & Lynch, L. M. (1996). Human-capital investments and productivity. *The American Economic Review*, *86*(2), 263-267.

Bloom, Y., Figgs, L. W., Baker, E. A., Dugbatey, K., Stanwyck, C. A., & Brownson, R. C. (2000). Data uses, benefits, and barriers for the behavioral risk factor surveillance system: a qualitative study of users. *Journal of public health management and practice: JPHMP*, 6(1), 78-86.

Blumenthal D. Launching HITECH. *N Engl J Med*. 2010;362(5): 382-385.

Blumenthal, D., & Tavenner, M. (2010). The “meaningful use” regulation for electronic health records. *New England Journal of Medicine*, 363(6), 501-504.

Bollen, K. A., & Long, J. S. (1993). *Testing structural equation models* (Vol. 154). Sage.

Boonstra, A., & Broekhuis, M. (2010). Barriers to the acceptance of electronic medical records by physicians from systematic review to taxonomy and interventions. *BMC health services research*, 10(1), 231.

Bossen, C., Jensen, L. G., & Udsen, F. W. (2013). Evaluation of a comprehensive EHR based on the DeLone and McLean model for IS success: approach, results, and success factors. *International journal of medical informatics*, *82*(10), 940-953.

Brevik, E., & Khosrow-Pour, M. (2005). User acceptance of technology and success in IS implementation. In *Managing Modern Organizations through Information Technology* (pp. 172-175). Idea Group Publishing.

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: The Guildford Press.

Browne, M. W., Cudeck, R., Bollen, K. A., & Long, J. S. (1993). Testing structural equation models

Brown, S. A., Dennis, A. R., & Venkatesh, V. (2010). Predicting collaboration technology use: Integrating technology adoption and collaboration research. *Journal of Management Information Systems*, *27*(2), 9-54.

Browne, M. W., MacCallum, R. C., Kim, C. T., Andersen, B. L., & Glaser, R. (2002). When fit indices and residuals are incompatible. *Psychological methods*, *7*(4), 403.

Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic perspectives*, *14*(4), 23-48.

Brynjolfsson, E., Malone, T. W., Gurbaxani, V., & Kambil, A. (1994). Does information technology lead to smaller firms?. *Management Science*, *40*(12), 1628-1644.

Bunker, D. (2013). Who Are We? Defining The IS Discipline By A Set Of Principles. *International Conference e-Society* 2013 13 – 16 March, Lisbon, Portugal.

Burney, A., Mahmood, N. & Abbas, Z. (2010) Information and Communication Technology in Healthcare Management Systems: Prospects for Developing Countries, *International Journal of Computer Applications*, 4 (2), pp 27-32.

Bussen, W., & Myers, M. D. (1997). Executive information system failure: a New Zealand case study. *Journal of Information Technology*, 12(2), 145–153.

Butler, M. (2014, October 8). Hospital Employees Fired for Illegally Accessing Ebola Patient's Health Records. *Journal of AHIMA*. Retrieved from http://journal.ahima.org/2014/10/08/hospital-employees-fired-for-illegally-ccessingebola-patients-health-records/

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming*. New York: Taylor and Francis Group, LLC.

Byrne, B. M. (2013). *Structural equation modeling with Mplus: Basic concepts, applications, and programming*. Routledge.

Camisón, C., & Forés, B. (2010). Knowledge absorptive capacity: New insights for its conceptualization and measurement. *Journal of Business Research*, 63(7), 707–715.

Cangur, S., & Ercan, I. (2015). Comparison of model fit indices used in structural equation modeling under multivariate normality. *Journal of Modern Applied Statistical Methods*, 14(1), 14.

Carayon, P., Cartmill, R., Blosky, M. A., Brown, R., Hackenberg, M., Hoonakker, P., ... & Walker, J. M. (2011). ICU nurses' acceptance of electronic health records. *Journal of the American Medical Informatics Association*, *18*(6), 812-819.

Carayon, P., Karsh, B. T., Cartmill, R. S., Hoonakker, P., Hundt, A. S., Krueger, D., & Wetterneck, T. B. (2010). Incorporating health information technology into workflow redesign-summary report. *Rockville, MD: Agency for Healthcare Research and Quality*, (10-0098).

Chakraborty, S., & Dobrzykowski, D. (2014). Linking service-dominant logic and healthcare supply chain. In *24th Annual Pom Conference Denver, Colorado, Usa*.

Chandy, R. K., & Tellis, G. J. (1998). Organizing for radical product innovation: The overlooked role of willingness to cannibalize. *Journal of marketing research*, *35*(4), 474-487.

Chang, I. C., & Hsu, H. M. (2012). Predicting medical staff intention to use an online reporting system with modified unified theory of acceptance and use of technology. *Telemedicine and e-Health*, *18*(1), 67-73.

Chaudoir, S. R., Dugan, A. G., & Barr, C. H. (2013). Measuring factors affecting implementation of health innovations: a systematic review of structural, organizational, provider, patient, and innovation level measures. *Implementation science*, *8*(1), 22.

Chen, C. D., Huang, C. K., Chen, M. J., & Ku, E. C. (2015). User's Adoption of Mobile O2O Applications: Perspectives of the Uses and Gratifications Paradigm and Service Dominant Logic. In *PACIS* (p. 253).

Chen, Y. S., Lin, M. J. J., & Chang, C. H. (2009). The positive effects of relationship learning and absorptive capacity on innovation performance and competitive advantage in industrial markets. *Industrial Marketing Management*, *38*(2), 152-158.

Chen, P., Tanasijevic, M. J., Schoenenberger, R. A., Fiskio, J., Kuperman, G. J., & Bates, D. W. (2003). A computer-based intervention for improving the appropriateness of antiepileptic drug level monitoring. *American Journal of Clinical Pathology*, *119*(3), 432-438.

Chennamsetty, H., Chalasani, S., & Riley, D. (2015, March). Predictive analytics on electronic health records (EHRs) using hadoop and hive. In *2015 IEEE International Conference on Electrical, Computer and Communication Technologies* (ICECCT) (pp. 1-5). IEEE.

Chesbrough, H. W. (2003). The era of open innovation. *MIT Sloan Management Review*, 44(3), 35.

Chesbrough, H., Vanhaverbeke, W., & West, J. (Eds.). (2006). Open innovation: Researching a new paradigm. *Oxford University Press on Demand.*

Chiva, R., Ghauri, P., & Alegre, J. (2014). Organizational learning, innovation and internationalization: A complex system model. *British Journal of Management*, *25*(4), 687-705.

Chung, B., Skibniewski, M. J., & Kwak, Y. H. (2009). Developing ERP systems success model for the construction industry. *Journal of Construction Engineering and Management*, *135*(3), 207-216.

Claxton, G., Rae, M., Long, M., Damico, A., Whitmore, H., & Foster, G. (2017). Health benefits in 2017: stable coverage, workers faced considerable variation in costs. *Health Affairs*, *36*(10), 1838-1847.

Cochran, W. G. (1977). *Sampling techniques* (3rd ed.). New York: John Wiley & Sons.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Erlbaum.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: the two faces of R & D. *The economic journal*, *99*(397), 569-596.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative science quarterly*, *35*(1), 128-152.

Compeau, D. R., & Higgins, C. A. (1995). Application of social cognitive theory to training for computer skills. *Information systems research*, *6*(2), 118-143.

Cortina, J. M. (1993). What is coefficient alpha? An examination of theory and applications. *Journal of applied psychology*, 78(1), 98.

Cooper, R. B., & Zmud, R. W. (1990). Information technology implementation research: a technological diffusion approach. *Management science*, *36*(2), 123-139.

Cozijnsen, A.J., Vrakking, W.J.,& Ijzerloo, M.V. (2000). Success and failure of 50 innovation projects in Dutch companies. *European Journal of Innovation Management*, 3 (3), 193-210.

Crane, J., & Crane, F. G. (2006). Preventing medication errors in hospitals through a systems approach and technological innovation: a prescription for 2010. *Hospital topics*, 84(4), 3-8.

Cresswell, K. M., Worth, A., & Sheikh, A. (2012). Comparative case study investigating sociotechnical processes of change in the context of a national electronic health record implementation. *Health Informatics Journal*, *18*(4), 251-270.

Cresswell, K. M., & Sheikh, A. (2014). Undertaking sociotechnical evaluations of health information technologies. *Journal of Innovation in Health Informatics*, *21*(2), 78-83.

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. P*sychometrika*, *16*(3), 297-334.

Cross, R., & Baird, Ll. (2000). Technology is not enough: Improving performance by building organizational memory. *Sloan Management Review*, 41(3), 69−78.

Cross, R., Liedtka, J., & Weiss, L. (2005). A practical guide to social networks. *Harvard Business Review*, 83(3), 124−132.

Cuckler, G. A., Sisko, A. M., Poisal, J. A., Keehan, S. P., Smith, S. D., Madison, A. J., ... & Hardesty, J. C. (2018). National health expenditure projections, 2017–26: despite uncertainty, fundamentals primarily drive spending growth. *Health Affairs*, *37*(3), 482-492.

Cutler, D.M. (2018). What Is The US Health Spending Problem?. *Health Affairs*, *37*(3), 493-497.

Dansky, K. H., Gamm, L. D., Vasey, J. J., & Barsukiewicz, C. K. (1999). Electronic medical records: Are physicians ready? *Journal of Healthcare Management*, 44(6), 440-455.

Darlington, R. B. (1990). *Regression and linear models*. New York: McGraw-Hill.

Davenport, T. H. (1993). *Process innovation: reengineering work through information technology*. Harvard Business Press.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* (Doctoral dissertation, Massachusetts Institute of Technology).

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319-340.

Davis, F. D. (1993). User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. *International journal of man-machine studies*, *38*(3), 475-487.

Davis, K., Doty, M. M., Shea, K., & Stremikis, K. (2009). Health information technology and physician perceptions of quality of care and satisfaction. *Health Policy*, *90*(2-3), 239-246.

Davison, G., & Hyland, P. (2002). Palliative care teams and organisational capability. *Team Performance Management: An International Journal*, *8*(3/4), 60-67.

De Jongh, P. J., De Jongh, E., Pienaar, M. P., Gordon-Grant, H., Oberholzer, M., & Santana, L. (2015). The impact of pre-selected variance in ation factor thresholds on the stability and predictive power of logistic regression models in credit scoring. *ORiON*, *31*(1), 17-37.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information systems research*, *3*(1), 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), 9-30.

Deshpandé, R., Farley, J. U., & Webster Jr, F. E. (1993). Corporate culture, customer orientation, and innovativeness in Japanese firms: a quadrad analysis. *Journal of marketing*, *57*(1), 23-37.

Devine, E. B., Hansen, R. N., Wilson-Norton, J. L., Lawless, N. M., Fisk, A. W., Blough, D. K., ... & Sullivan, S. D. (2010). The impact of computerized provider order entry on medication errors in a multispecialty group practice. *Journal of the American Medical Informatics Association*, 17(1), 78-84.

Dexter, P. R., Perkins, S., Overhage, J. M., Maharry, K., Kohler, R. B., & McDonald, C. J. (2001). A computerized reminder system to increase the use of preventive care for hospitalized patients. *New England Journal of Medicine*, 345(13), 965-970.

Djellal, F., & Gallouj, F. (2007). Innovation in hospitals: a survey of the literature. *The European Journal of Health Economics*, *8*(3), 181-193.

do Carmo Caccia-Bava, M., Guimaraes, T., & Harrington, S. J. (2006). Hospital organization culture, capacity to innovate and success in technology adoption. *Journal of Health Organization and Management*, *20*(3), 194-217.

Dwivedi, Y. K., Wastell, D., Laumer, S., Henriksen, H. Z., Myers, M. D., Bunker, D., ... & Srivastava, S. C. (2015). Research on information systems failures and successes: Status update and future directions. *Information Systems Frontiers*, 17(1), 143-157.

Eckhardt, A., Laumer, S., & Weitzel, T. (2009). Who influences whom? Analyzing workplace referents' social influence on it adoption and non-adoption. *Journal of Information Technology*, *24*(1), 11–24.

Elbanna, A. (2012). Top Management Support in Multiple-Project Environments: An in-Practice View. *European Journal of Information Systems*, 22(3), 278-294.

Elberg, P. B. (2001). Electronic patient records and innovation in health care services. *International Journal of Medical Informatics*, 64(2-3), 201-205.

Elder, K. T., Wiltshire, J. C., Rooks, R. N., BeLue, R., & Gary, L. C. (2010). Health information technology and physician career satisfaction. *Perspectives in health information management/AHIMA, American Health Information Management Association*, *7*(Summer).

Emani, S., Yamin, C. K., Peters, E., Karson, A. S., Lipsitz, S. R., Wald, J. S., ... & Bates, D. W. (2012). Patient perceptions of a personal health record: a test of the diffusion of innovation model. *Journal of medical Internet research*, 14(6).

Estrin, D., & Sim, I. (2010). Open mHealth architecture: an engine for health care innovation. *Science*, 330(6005), 759-760.

Ewing, T., & Cusick, D. (2004). Knowing what to measure: by investing in a new clinical information system, one organization was able to improve patient care without adding staff while also increasing efficiency and productivity. *Healthcare Financial Management*, 58(6), 60-64.

Field, A., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. Sage publications.

Fishbein, M., and Ajzen, I. Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research, Addison-Wesley, Reading, MA, 1975.

Flowers, S. (1996). *Software failure, management failure: amazing stories and cautionary tales*. John Wiley.

Ford, E. W., McAlearney, A. S., Phillips, M. T., Menachemi, N., & Rudolph, B. (2008). Predicting computerized physician order entry system adoption in US hospitals: Can the federal mandate be met?. *International Journal of Medical Informatics*, *77*(8), 539-545.

Fosfuri, A., & Tribó, J. A. (2008). Exploring the antecedents of potential absorptive capacity and its impact on innovation performance. *Omega*, *36*(2), 173-187.

Freund, R.J. and Wilson, W.J. and Sa, P. (2006) Regression Analysis. Statistical Modeling of a response variable, 2nd edition, Elsevier.

Friedberg, M. W., Chen, P. G., Van Busum, K. R., Aunon, F., Pham, C., Caloyeras, J., ... & Crosson, F. J. (2014). Factors affecting physician professional satisfaction and their implications for patient care, health systems, and health policy. *Rand health quarterly*, *3*(4).

Gable, G. G. (1994). Integrating case study and survey research methods: an example in information systems. *European Journal of Information Systems, 3*(2), 112-126.

Gagnon, M. P., Ghandour, E. K., Talla, P. K., Simonyan, D., Godin, G., Labrecque, M., ... & Rousseau, M. (2014). Electronic health record acceptance by physicians: Testing an integrated theoretical model. *Journal of biomedical informatics*, *48*, 17-27.

Gagnon, M. P., Godin, G., Gagné, C., Fortin, J. P., Lamothe, L., Reinharz, D., & Cloutier, A. (2003). An adaptation of the theory of interpersonal behaviour to the study of telemedicine adoption by physicians. *International journal of medical informatics*, 71(2-3), 103-115.

Galewitz, P. H. (2011). Medical practices increasingly allow online appointments. *Kaiser Health News*.

Gangwar, H., Date, H., & Raoot, A. D. (2014). Review on IT adoption: insights from recent technologies. *Journal of Enterprise Information Management*, *27*(4), 488-502.

Garrett, P., & Seidman. J. (2011). Electronic Health & Medical Records. (n.d.). Retrieved from https://www.healthit.gov/buzz-blog/electronic-health-and-medical-records/emr-vs-ehrdifference

Garson, G. D. (2009). *Statnotes: Topics in Multivariate Analysis.* Retrieved from http://faculty.chass.ncsu.edu/garson/pa765/statnote.htm.

Gassmann, O., Enkel, E., & Chesbrough, H. (2010). The future of open innovation. *R&d Management*, 40(3), 213-221.

Genes, N., Violante, S., Cetrangol, C., Rogers, L., Schadt, E. E., & Chan, Y. F. Y. (2018). From smartphone to EHR: a case report on integrating patient-generated health data. *Npj Digital Medicine*, *1*(1), 23.

George, D., & Mallery, M. (2003). Using SPSS for Windows step by step: a simple guide and reference.

Gerbing, D. W., & Anderson, J. C. (1992). Monte Carlo evaluations of goodness of fit indices for structural equation models. *Sociological Methods and Research, 21*(2), 132-160. doi:10.1177/0049124192021002002

Ghalandari, K. (2012). The effect of performance expectancy, effort expectancy, social influence and facilitating conditions on acceptance of e-banking services in Iran: The moderating role of age and gender. *Middle-East Journal of Scientific Research*, *12*(6), 801-807.

Gil, M. J. Á., Aksoy, D., & Kulcsar, B. (2009, September). ERP and four dimensions of absorptive capacity: lessons from a developing country. In *World Summit on Knowledge Society* (pp. 387-394). Springer, Berlin, Heidelberg.

Godambe, V. P. (1982). Estimation in survey sampling: robustness and optimality. *Journal of the American Statistical Association*, 77(378), 393-403.

Goedert, J. (2014). What to do about stage 2. Providers have ideas for software vendors and regulators on how to make the next stage of meaningful use a bit more realistic. *Health data management*, *22*(8), 14.

Goetz, D. G., Kuzel, A. J., Feng, L. B., DeShazo, J. P., & Love, L. E. (2012). EHRs in primary care practices: benefits, challenges, and successful strategies. *The American journal of managed care*, 18(2), e48-54.

Goh, S. C. (1998). Toward a learning organization: The strategic building blocks. *SAM Advanced Management Journal*, *63*(2), 15-21.

Goh, S., & Richards, G. (1997). Benchmarking the learning capability of organizations. *European Management Journal, 15*(5), 575-583.

Gould, J. D., Boies, S. J., & Lewis, C. (1991). Making usable, useful, productivity-enhancing computer applications. *Communications of the ACM*, 34(1), 74–85.

Grant, R. M. (1996). Toward a knowledge-based theory of the firm. *Strategic management journal*, *17*(S2), 109-122.

Grapentine, T. (2000). Path analysis vs. structural equation modeling. *Marketing Research*, *12*(3), 12-20.

Greenhalgh, T., Robert, G., MacFarlane, F., Bate, P., & Kyriakidou, O. (2004). Diffusion of innovations in service organizations: Systematic review and recommendations. *The Milbank Quarterly*, 82(4), 581-629.

Gunasekaran, A., Ngai, E. W., & McGaughey, R. E. (2006). Information technology and systems justification: A review for research and applications. *European Journal of Operational Research*, *173*(3), 957-983.

Hackl, W. O., Hoerbst, A., & Ammenwerth, E. (2011). Why the hell do we need electronic health records?. *Methods of Information in Medicine*, *50*(01), 53-61.

Hair, J. E. Jr., Anderson, R. E., & Tatham, R. L. (1995). Multivariate data analysis (fifth edition). New York: Macmillan Publishing Company.

Hallquist, M. (2017, October 12). SEM Fit and Modification. Retrieved from https://psu-psychology.github.io/psy-597-SEM/08_fit/sem_fit_modification.html

Hameed, M. A., Counsell, S., & Swift, S. (2012). A conceptual model for the process of IT innovation adoption in organizations. *Journal of Engineering and Technology Management*, *29*(3), 358-390.

Hardyman, W., Daunt, K. L., & Kitchener, M. (2015). Value co-creation through patient engagement in health care: a micro-level approach and research agenda. *Public Management Review*, *17*(1), 90-107.

Healthcare Research. (2004, November 30). 2004 National Healthcare Quality Report. Retrieved from https://www.hsdl.org/?abstract&did=457594

Hebert, M., & Benbasat, I. (1994). Adopting information technology in hospitals: the relationship between attitudes/expectations and behavior. *Hospital & health services administration*, *39*(3), 369-384.

Henfridsson, O., & Lind, M. (2014). Information systems strategizing, organizational sub-communities, and the emergence of a sustainability strategy. *The Journal of Strategic Information Systems*, *23*(1), 11-28.

Henfridsson, O., & Lindgren, R. (2010). User involvement in developing mobile and temporarily interconnected systems. *Information Systems Journal*, *20*(2), 119-135.

Hill Jr, R. G., Sears, L. M., & Melanson, S. W. (2013). 4000 clicks: a productivity analysis of electronic medical records in a community hospital ED. *The American journal of emergency medicine*, 31(11), 1591-1594.

Hillestad, R., Bigelow, J., Bower, A., Girosi, F., Meili, R., Scoville, R., & Taylor, R. (2005). Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. *Health affairs*, 24(5), 1103-1117.

Hilton, T., & Hughes, T. (2008). Co-production and co-creation using self service technology: The application of service-dominant logic. In *Otago Forum 2*.

Hilton, T., Hughes, T., Little, E., & Marandi, E. (2013). Adopting self-service technology to do more with less. *Journal of Services Marketing*, *27*(1), 3-12.

Hitt, L. M. (1999). Information technology and firm boundaries: Evidence from panel data. *Information Systems Research*, *10*(2), 134-149.

Hofstede, G. (2009). Geert Hofstede cultural dimensions.

Holanda, A. A., e Sá, H. L. D. C., Vieira, A. P. G. F., & Catrib, A. M. F. (2012). Use and satisfaction with electronic health record by primary care physicians in a health district in Brazil. *Journal of medical systems*, *36*(5), 3141-3149.

Holden, R. J. (2011). What stands in the way of technology-mediated patient safety improvements? A study of facilitators and barriers to physicians' use of electronic health records. *Journal of patient safety*, *7*(4), 193.

Holden, R. J., Brown, R. L., Scanlon, M. C., & Karsh, B. T. (2012). Modeling nurses' acceptance of bar coded medication administration technology at a pediatric hospital. *Journal of the American Medical Informatics Association*, *19*(6), 1050-1058.

Holden, R. J., & Karsh, B. T. (2010). The technology acceptance model: its past and its future in health care. *Journal of biomedical informatics*, *43*(1), 159-172.

Holotiuk, F., & Moormann, J. (2018). Organizational adoption of digital innovation: The case of blockchain technology. In *Proceedings of the European conference on information systems*.

Holtz, B., & Krein, S. (2011). Understanding nurse perceptions of a newly implemented electronic medical record system. *Journal of Technology in Human Services*, *29*(4), 247-262.

Hox, J. J., & Bechger, T. M. (1998). An introduction to structural equation modeling. *Family Science Review*, *11*, 354-373.

Hoyle, R. H., & Gottfredson, N. C. (2015). Sample size considerations in prevention research applications of multilevel modeling and structural equation modeling. *Prevention Science*, *16*(7), 987-996.

Hsiao, J. L., Chang, H. C., & Chen, R. F. (2011). A study of factors affecting acceptance of hospital information systems: a nursing perspective. *Journal of Nursing Research*, *19*(2), 150-160.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1-55.

Hu, P. J., Chau, P. Y., Sheng, O. R. L., & Tam, K. Y. (1999). Examining the technology acceptance model using physician acceptance of telemedicine technology. *Journal of management information systems*, *16*(2), 91-112.

Huang, H. T. D. (2010). *Modeling the relationships among topical knowledge, anxiety, and integrated speaking test performance: A structural equation modeling approach*. The University of Texas at Austin.

Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. *Organization science*, *2*(1), 88-115.

Huizingh, E. K. (2011). Open innovation: State of the art and future perspectives. *Technovation*, *31*(1), 2-9.

Hurley, R. F., & Hult, G. T. M. (1998). Innovation, market orientation, and organizational learning: an integration and empirical examination. *Journal of marketing*, *62*(3), 42-54.

Hutcheson, G. D., & Sofroniou, N. (1999). *The multivariate social scientist: Introductory statistics using generalized linear models*. Sage.

Hyman, L., Lamb, J., & Bulmer, M. (2006, April). The use of pre-existing survey questions: Implications for data quality. In *Proceedings of the European Conference on Quality in Survey Statistics* (pp. 1-8).

Jahanbakhsh, M., Peikari, H. R., Hazhir, F., & Saghaeiannejad-Isfahani, S. (2018). An investigation into the effective factors on the acceptance and use of integrated health system in the primary health-care centers. *Journal of Education and Health Promotion*, *7*.

Jamoom, E., & Yang, N. (2016). Table of electronic health record adoption and use among office-based physicians in the US, by state: 2015 National Electronic Health Records Survey. *Hyattsville, MD: National Center for Health Statistics*.

Jarvenpaa, S. L., Dickson, G. W., & DeSanctis, G. (1985). Methodological issues in experimental IS research: experiences and recommendations. *MIS quarterly*, 141-156.

Jarvenpaa, S. L., & Leidner, D. E. (1998). An information company in Mexico: Extending the resource-based view of the firm to a developing country context. *Information Systems Research*, *9*(4), 342-361.

Jerez-Gomez, P., Cespedes-Lorente, J., & Valle-Cabrera, R. (2005). Organizational learning capability: a proposal of measurement. *Journal of business research*, *58*(6), 715-725.

Johns, G. (2006). The Essential Impact of Context on Organizational Behavior. *Academy of Management Review*, 31(2), 386-408.

Johnson, K. B. (2001). Barriers that impede the adoption of pediatric information technology. *Archives of pediatrics & adolescent medicine*, *155*(12), 1374-1379.

Joiner, K. A., & Lusch, R. F. (2016). Evolving to a new service-dominant logic for health care. *Innovation and Entrepreneurship in Health*, *3*(3), 25-33.

Jones, S. S., Koppel, R., Ridgely, M. S., Palen, T. E., Wu, S. Y., & Harrison, M. I. (2011). Guide to reducing unintended consequences of electronic health records.

Joseph, S., Sow, M., Furukawa, M. F., Posnack, S., & Chaffee, M. S. (2014). HITECH spurs EHR vendor competition and innovation, resulting in increased adoption. *Am J Manag Care*, *20*(9), 734-740.

Kaiser, H. F. (1970). A second generation little jiffy. *Psychometrika, 35*(4), 401–415. https://doi.org/10.1007/BF02291817

Kamal, E. M., & Flanagan, R. (2014, April). Model of absorptive capacity and implementation of new technology for rural construction SMEs. In *Australasian Journal of Construction Economics and Building-Conference Series* (Vol. 2, No. 2, pp. 19-26).

Kaplan, B., & Harris-Salamone, K. D. (2009). Health IT success and failure: recommendations from literature and an AMIA workshop. *Journal of the American Medical Informatics Association*, *16*(3), 291-299.

Karjaluoto, H., Püschel, J., Mazzon, J. A., & Hernandez, J. M. C. (2010). Mobile banking: proposition of an integrated adoption intention framework. *International Journal of bank marketing*.

Karpen, I. O., Bove, L. L., & Lukas, B. A. (2012). Linking service-dominant logic and strategic business practice: A conceptual model of a service-dominant orientation. *Journal of service research*, *15*(1), 21-38.

Karpen, I. O., Bove, L. L., Lukas, B. A., & Zyphur, M. J. (2015). Service-dominant orientation: measurement and impact on performance outcomes. *Journal of Retailing*, *91*(1), 89-108.

Kash, B. A., Spaulding, A., Gamm, L. D., & Johnson, C. (2014). Leadership, culture, and organizational technologies as absorptive capacity for innovation and transformation in the healthcare sector: A framework for research. *Change Management*, *13*(1), 1-13.

Ke, W., & Wei, K. K. (2006). Organizational learning process: its antecedents and consequences in enterprise system implementation. *Journal of Global Information Management (JGIM)*, *14*(1), 1-22.

Keen, P. G. W. (1981). Information systems and organizational change. *Communications of the ACM, 24*(1), 24–33.

Keith, T. Z. (1999). Structural equation modeling in school psychology. In C. R. Reynolds & T. B. Gutkin (Eds.), *The handbook of school psychology* (3rd ed., pp. 78-107). New York, Wiley.

Keith, T. Z. (2006). *Multiple regression and beyond*. Boston, MA: Pearson Education, Inc.

Kellar, S. P., & Kelvin E. A. (2013). *Munro's statistical methods for health care research* (6th ed.). Philadelphia, PA: Lippincott Williams & Wilkins.

Kenny, D. A. (2011). Terminology and basics of SEM. *Terminology*.

Kenny, D. A. (2015). *Measuring model fit*. Retrieved from http://davidakenny.net/cm/fit.htm

Ketikidis, P., Dimitrovski, T., Lazuras, L., & Bath, P. A. (2012). Acceptance of health information technology in health professionals: An application of the revised technology acceptance model. *Health informatics journal*, *18*(2), 124-134.

Khamis, N., Sulaiman, A., & Mohezar, S. (2014). Achieving e-Business Excellence through Knowledge Management and Organizational Learning Capabilities: A Malaysian Perspective. *International Journal of Economics & Management*, *8*(2).

Kharrazi, H., Gonzalez, C. P., Lowe, K. B., Huerta, T. R., & Ford, E. W. (2018). Forecasting the maturation of electronic health record functions among US hospitals: retrospective analysis and predictive model. *Journal of medical Internet research*, *20*(8).

Khosravi, P., Rezvani, A., Subasinghage, M., & Perera, M. (2012, January). Individuals' absorptive capacity in enterprise system assimilation. In *ACIS 2012: Location, location, location: Proceedings of the 23rd Australasian conference on information systems 2012* (pp. 1-7). ACIS.

Kim, S., Lee, K. H., Hwang, H., & Yoo, S. (2015). Analysis of the factors influencing healthcare professionals' adoption of mobile electronic medical record (EMR) using the unified theory of acceptance and use of technology (UTAUT) in a tertiary hospital. *BMC medical informatics and decision making*, *16*(1), 12.

King, J., Patel, V., Jamoom, E. W., & Furukawa, M. F. (2014). Clinical benefits of electronic health record use: national findings. *Health services research*, 49(1pt2), 392-404.

Kirsch, L.J., Sambamurthy, V., Ko, D.-G., & Purvis, R.L. (2002). Controlling Information Systems Development Projects: The View from the Client. *Management Science*, 48(4), 484-498.

Kitzinger, J. (1995). Qualitative Research: Introducing Focus Groups. *British Medical Journal, 311*(29 July), 299-302.

Kline, R. B. (2005). *Principles and Practice of Structural Equation Modeling* (2nd ed.). New York, NY: The Guilford Press.

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th edition). New York, NY: The Guilford Press.

Knutsen, L. A. (2005, January). M-service expectancies and attitudes: Linkages and effects of first impressions. In *Proceedings of the 38th annual Hawaii international conference on ystem sciences* (pp. 84a-84a). IEEE.

Kowitlawakul, Y., Chan, S. W. C., Pulcini, J., & Wang, W. (2015). Factors influencing nursing students' acceptance of electronic health records for nursing education (EHRNE) software program. *Nurse education today*, *35*(1), 189-194.

Krist, A. H. (2015). Electronic health record innovations for healthier patients and happier doctors. *Am Board Family Med*, 28 (3).

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), 252.

Kukafka, R., Ancker, J. S., Chan, C., Chelico, J., Khan, S., Mortoti, S., ... & Stephens, K. (2007). Redesigning electronic health record systems to support public health. *Journal of biomedical informatics*, 40(4), 398-409.

Kutner, M.H and Nachtsheim, C.J. and Neter, J. and Li, W. (2005) *Applied linear statistical models*, 5th edition, McGraw-Hill.

Labrique, A. B., Vasudevan, L., Kochi, E., Fabricant, R., & Mehl, G. (2013).mHealth innovations as health system strengthening tools: 12 common applications and a visual framework. *Global health: science and practice*, *1*(2), 160-171.

Lai, K., & Green, S. B. (2016). The problem with having two watches: Assessment of fit when RMSEA and CFI disagree. *Multivariate behavioral research*, 51(2-3), 220-239.

Lapointe, L., & Rivard, S. (2005). A multilevel model of resistance to information technology implementation. *MIS quarterly*, 461-491.

Laranjo, L., Rodrigues, D., Pereira, A. M., Ribeiro, R. T., & Boavida, J. M. (2016). Use of electronic health records and geographic information systems in public health surveillance of type 2 diabetes: a feasibility study. *JMIR public health and surveillance*, 2(1), e12.

Laumer, S., & Eckhardt, A. (2012). Why do people reject technologies: a review of user resistance theories. In *Information systems theory* (pp. 63-86). Springer, New York, NY.

Lee, F. W. (2000). Adoption of electronic medical records as a technology innovation for ambulatory care at the Medical University of South Carolina. *Topics in health information management*, *21*(1), 1-20.

Lee, J. C., & Chen, C. Y. (2019). Exploring the determinants of software process improvement success: A dynamic capability view. *Information Development*, *35*(1), 6-20.

Lee, C. C., Lin, S. P., Yang, S. L., Tsou, M. Y., & Chang, K. Y. (2013). Evaluating the influence of perceived organizational learning capability on user acceptance of information technology among operating room nurse staff. *Acta Anaesthesiologica Taiwanica*, 51(1), 22-27.

Lee, J.C., & Myers, M.D. (2004). Dominant Actors, Political Agendas, and Strategic Shifts over Time: A Critical Ethnography of an Enterprise Systems Implementation. *Journal of Strategic Information Systems*, 13(4), 355-374.

Lee, J., Wyner, G.M., & Pentland, B.T. (2008). Process Grammar as a Tool for Business Process Design. *MIS Quarterly*, 32, 757-778.

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & management*, *40*(3), 191-204.

Lewis, B. (2003). “The 70-percent failure”, InfoWorld. Retrieved from http://archive.infoworld.com/articles/op/xml/01/10/29/011029/opsurvival.xml

Lewis, K. (2003). Measuring transactive memory systems in the field: scale development and validation. *Journal of applied psychology*, *88*(4), 587.

Lewis, J. L., & Sheppard, S. R. (2006). Culture and communication: can landscape visualization improve forest management consultation with indigenous communities?. *Landscape and Urban Planning*, 77(3), 291-313.

Liao, H. L., & Lu, H. P. (2008). The role of experience and innovation characteristics in the adoption and continued use of e-learning websites. *Computers & Education*, *51*(4), 1405-1416.

Lichtenberg, F. R. (1995). The output contributions of computer equipment and personnel: A firm-level analysis. *Economics of innovation and new technology*, *3*(3-4), 201-218.

Linzer, M., Konrad, T. R., Douglas, J., McMurray, J. E., Pathman, D. E., Williams, E. S., ... & Rhodes, E. (2000). Managed care, time pressure, and physician job satisfaction: results from the physician worklife study. *Journal of general internal medicine*, 15(7), 441-450.

Lucas Jr, H. C. (1978). Empirical evidence for a descriptive model of implementation. *MIS Quarterly*, 27-42.

Lucas Jr, H. C., & Goh, J. M. (2009). Disruptive technology: How Kodak missed the digital photography revolution. *The Journal of Strategic Information Systems*, *18*(1), 46-55.

Lusch, R. F., & Nambisan, S. (2015). Service innovation: A service-dominant logic perspective. *MIS quarterly*, *39*(1).

Lusch, R. F., Vargo, S. L., & Tanniru, M. (2010). Service, value networks and learning. *Journal of the academy of marketing science*, *38*(1), 19-31.

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods,1* (2), 130-149.

MacCallum, R. C., Roznowski, M., & Necowitz, L. B. (1992). Model modifications in covariance structure analysis: the problem of capitalization on chance. *Psychological bulletin*, *111*(3), 490.

Maglio, P. P., & Spohrer, J. (2008). Fundamentals of service science. *Journal of the academy of marketing science*, *36*(1), 18-20.

Maillet É, Mathieu L, Sicotte C. Modeling factors explaining the acceptance, actual use and satisfaction of nurses using an Electronic Patient Record in acute care settings: An extension of the UTAUT. *Int J Med Inform*. 2015;84(1):36.-47 doi: 10.1016/j.ijmedinf.2014.09.004.

Marabelli, M., & Newell, S. (2013). Knowledge creation and ES implementation: the absorptive capacity lens.

Markus, M. L. (1983). Power, politics, and mis implementation. *Communications of the ACM*, *26*(6), 430–444.

Markus, M. L., Tanis, C., & Van Fenema, P. C. (2000). Enterprise resource planning: multisite ERP implementations. *Communications of the ACM*, *43*(4), 42-46.

Marsh, H. W., Hau, K. T., & Wen, Z. (2004). In search of golden rules: Comment on hypothesis-testing approaches to setting cutoff values for fit indexes and dangers in overgeneralizing Hu and Bentler's (1999) findings. *Structural equation modeling*, 11(3), 320-341.

Martinko, M. J., Zmud, R. W., & Henry, J. W. (1996). An attributional explanation of individual resistance to the introduction of information technologies in the workplace. *Behaviour & Information Technology*, *15*(5), 313-330.

Marufu, M. A., & van der Merwe, A. (2019). Using service-dominant logic to build empathy for design thinking in a health service delivery environment. In *Third International Congress on Information and Communication Technology* (pp. 499-515). Springer, Singapore.

Mason, R.L. and Gunst, R.F. and Hess, J.L. (1989) Statistical design and analysis of experiments: Applications to Engineering and Science, 2nd edition, Wiley.

Mason, P., Mayer, R., Chien, W. W., & Monestime, J. P. (2017). Overcoming barriers to implementing electronic health records in rural primary care clinics. *The Qualitative Report*, 22(11), 2943-2955.

Mat, A., & Razak, R. C. (2011). The influence of organizational learning capability on success of technological innovation (product) implementation with moderating effect of knowledge complexity. *International Journal of Business and Social Science*, *2*(17).

McCann, E. (2014, December 19). Data hijacker holds patient PHI hostage. *Healthcare IT News*. Retrieved from http://www.healthcareitnews.com/news/data-hijacker-holds-patient-phihostage

McCardle, K. F. (1985). Information acquisition and the adoption of new technology. *Management science*, *31*(11), 1372-1389.

McCarroll, T. (1991). What new age. *Time*, *138*(12), 44-46.

McColl-Kennedy, J. R., Vargo, S. L., Dagger, T. S., Sweeney, J. C., & Kasteren, Y. V. (2012). Health care customer value cocreation practice styles. *Journal of Service Research*, *15*(4), 370-389.

McGinn, C. A., Grenier, S., Duplantie, J., Shaw, N., Sicotte, C., Mathieu, L., ... & Gagnon, M. P. (2011). Comparison of user groups' perspectives of barriers and facilitators to implementing electronic health records: a systematic review. *BMC medicine*, *9*(1), 46.

Melas, C. D., Zampetakis, L. A., Dimopoulou, A., & Moustakis, V. (2011). Modeling the acceptance of clinical information systems among hospital medical staff: an extended TAM model. *Journal of biomedical informatics*, *44*(4), 553-564.

Menachemi, N., Chukmaitov, A., Saunders, C., & Brooks, R. G. (2008). Hospital quality of care: does information technology matter? The relationship between information technology adoption and quality of care. *Health care management review*, 33(1), 51-59.

Menachemi, N., & Collum, T. H. (2011). Benefits and drawbacks of electronic health record systems. *Risk management and healthcare policy*, *4*, 47.

Menachemi, N., Powers, T. L., & Brooks, R. G. (2009). The role of information technology usage in physician practice satisfaction. *Health care management review*, *34*(4), 364-371.

Mildon, J., & Cohen, T. (2001). Drivers in the electronic medical records market. *Health management technology*, 22(5), 14-6.

Miles, J., & Shevlin, M. (2001). *Applying regression & correlation: A guide for students and researchers*. London: Sage Publications, Ltd.

Miller, R. H., & Sim, I. (2004). Physicians' use of electronic medical records: barriers and solutions. *Health affairs,* 23(2), 116-126.

Miskulin, D. C., Weiner, D. E., Tighiouart, H., Ladik, V., Servilla, K., Zager, P. G., ... & Meyer, K. B. (2009). Computerized decision support for EPO dosing in hemodialysis patients. *American Journal of Kidney Diseases,* 54(6), 1081-1088.

Mitchell, V. L. (2006). Knowledge integration and information technology project performance. *MIS Quarterly,* 30(4), 919–939.

Mohammad Mosadeghrad, A. (2013). Healthcare service quality: towards a broad definition. *International journal of health care quality assurance*, *26*(3), 203-219.

Moody, L. E., Slocumb, E., Berg, B., & Jackson, D. (2004). Electronic health records documentation in nursing: nurses' perceptions, attitudes, and preferences. *CIN: Computers, Informatics, Nursing*, *22*(6), 337-344.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192-222.

Morton, M. E. (2008). Use and acceptance of an electronic health record: factors affecting physician attitudes.

Morton, M. E., & Wiedenbeck, S. (2009). A framework for predicting EHR adoption attitudes: a physician survey. *Perspectives in health information management/AHIMA, American Health Information Management Association*, *6*(Fall).

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, 86-98.

Moshki, M. K., Teimouri, H., & Ansari, R. (2013). A survey on the level of Information Technology Acceptance and proposition of a Comprehensive model (The Case of Nir Pars Company). *International Journal of Academic Research in Business and Social Sciences*, 3(9), 214.

Motahhari Nejad, H. (2018). The Role of Organizational Learning Capability on Acceptance of Information Technology (Case Study: Nurses of Teaching Hospitals). *Journal of Health Administration*, 20(70), 107-122.

Mukhopadhyay, T., Rajiv, S., & Srinivasan, K. (1997). Information technology impact on process output and quality. *Management Science, 43*(12), 1645-1659.

Mullings, C., & Ngwenyama, O. (2018, July). Factors that Drive Successful Electronic Health Record Implementation Among Aging Nurses. In *International Conference on HCI in Business, Government, and Organizations* (pp. 626-644). Springer, Cham.

Munkvold, B. E. (1999). Challenges of IT implementation for supporting collaboration in distributed organizations. *European Journal of Information Systems*, *8*(4), 260-272.

Neumeier, M. (2013). Using Kotter's change management theory and innovation diffusion theory in implementing an electronic medical record. *Canadian Journal of Nursing Informatics*, 8(1), 1-9.

Niès, J., Colombet, I., Zapletal, E., Gillaizeau, F., Chevalier, P., & Durieux, P. (2010). Effects of automated alerts on unnecessarily repeated serology tests in a cardiovascular surgery department: a time series analysis. *BMC health services research*, 10(1), 70.

Nikookar, G., Rahrovy, E., Razi, S., & Ghassemi, R. A. (2015). Investigating influential factors on word of mouth in service industries: the case of Iran Airline company. *Procedia-Social and Behavioral Sciences*, 177, 217-222.

Nunkoo, R. (Ed.). (2018). Handbook of Research Methods for Tourism and Hospitality Management. Edward Elgar Publishing.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psycometric theory* (3rd ed.) New York, NY: McGraw-Hill.

Nunnally, J. C., Bernstein, I. H., & Berge, J. M. T. (1967). *Psychometric theory* (Vol. 226). New York: McGraw-Hill.

Nyende, H. (2018). The role of technology in value co-creation of maternal healthcare: A service-dominant logic perspective.

OECD (2019), "Health expenditure per capita", in *Health at a Glance 2019: OECD Indicators*, OECD Publishing, Paris.

Olobatuyi, M. E. (2006). *A user's guide to path analysis*. Lanham, MD: University Press of America, Inc.

Orlikowski, W.J., & Robey, D. (1991). Information Technology and the Structuring of Organizations. *Information Systems Research*, 2(2), 143-169.

Ornelas, E., & Skaggs, M. (2017). Factors Associated With the Successful Implementation of Telehealth in a Retail Health Clinic.

Ozkan, S., Kurt, N. & Iyigun, C. (2012), Facilitating Adoption of Enterprise Resource Planning (ERP) Systems: The State of the Art. *Proceedings of the Americas Conference on Information Systems,* Seattle.

Pablo, A. L., Reay, T., Dewald, J. R., & Casebeer, A. L. (2007). Identifying, enabling and managing dynamic capabilities in the public sector. *Journal of management studies*, *44*(5), 687-708.

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

Paré, G., Sicotte, C., & Jacques, H. (2006). The effects of creating psychological ownership on physicians' acceptance of clinical information systems. *Journal of the American Medical Informatics Association*, *13*(2), 197-205.

Pathman, D. E., Williams, E. S., & Konrad, T. R. (1996). Rural physician satisfaction: its sources and relationship to retention. *The Journal of rural health*, 12(5), 366-377.

Pavlou, P. A., & El Sawy, O. A. (2006). From IT leveraging competence to competitive advantage in turbulent environments: The case of new product development. *Information Systems Research*, *17*(3), 198-227.

Peng, G., Dey, D., & Lahiri, A. (2014). Healthcare IT adoption: An analysis of knowledge transfer in socioeconomic networks. *Journal of Management Information Systems*, *31*(3), 7-34.

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: models, dimensions, measures, and interrelationships. *European journal of information systems*, *17*(3), 236-263.

Pfoh, E. R., Abramson, E., Zandieh, S., Edwards, A., & Kaushal, R. (2012). Satisfaction after the transition between electronic health record systems at six ambulatory practices. *Journal of evaluation in clinical practice*, *18*(6), 1133-1139.

Phichitchaisopa, N., & Naenna, T. (2013). Factors affecting the adoption of healthcare information technology. *EXCLI journal*, *12*, 413.

Piller, F., & West, J. (2014). Firms, users, and innovation. *New frontiers in open innovation*, *29*(1), 29-49.

Pinsonneault, A., & Kraemer, K. L. (1993). Survey Research Methodology in Management Information Systems: An Assessment. *Journal of Management Information Systems, 10*(2), 75-105.

Plyviou, A., Pouloudi, N. and Pramatari, K. (2014), “Cloud Adoption: Relative Advantage or IT Fashion?”, *Proceedings of the European Conference on Information Systems*, Tel Aviv.

Porter, M. E. (2010). What is value in health care?. *New England Journal of Medicine*, *363*(26), 2477-2481.

Porter, M. E., & Lee, T. H. (2013). The strategy that will fix health care. *Harvard business review*, *91*(10), 1-19.

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage.

Proctor, E., Silmere, H., Raghavan, R., Hovmand, P., Aarons, G., Bunger, A., ... & Hensley, M. (2011). Outcomes for implementation research: conceptual distinctions, measurement challenges, and research agenda. *Administration and Policy in Mental Health and Mental Health Services Research*, *38*(2), 65-76.

Rahimi, B., Timpka, T., Vimarlund, V., Uppugunduri, S., & Svensson, M. (2009). Organization-wide adoption of computerized provider order entry systems: a study based on diffusion of innovations theory. *BMC Medical Informatics and Decision Making*, *9*(1), 52.

Rao, U. K. (2012). Concepts in sample size determination. *Indian Journal of Dental Research*, *23*(5), 660.

Reeves, T. C., & Ford, E. W. (2004). Strategic management and performance differences: Nonprofit versus for-profit health organizations. *Health care management review*, *29*(4), 298-308.

Revicki, D. (2014) Internal Consistency Reliability. In: Michalos A.C. (eds) *Encyclopedia of Quality of Life and Well-Being Research*. Springer, Dordrecht.

Ridder, H. G., Doege, V., & Martini, S. (2007). Differences in the implementation of diagnosis-related groups across clinical departments: a German hospital case study. *Health services research*, *42*(6p1), 2120-2139.

Robey, D., Ross, J. W., & Boudreau, M. C. (2002). Learning to implement enterprise systems: An exploratory study of the dialectics of change. *Journal of management information systems*, *19*(1), 17-46.

Rogers, E. M. (1995). Diffusion of innovations, 4th The Free Press. *New York*.

Rogers, E. M. (2003). Diffusion of Innovations, 5th edn. Simon & Shuster. *Inc., New York*.

Ruggiero, T. E. (2000). Uses and gratifications theory in the 21st century. *Mass communication & society*, *3*(1), 3-37.

Saad, N. M., Alias, R. A., & Ismail, Z. (2013, November). Initial framework on identifying factors influencing individuals' usage of telehealth. In *2013 International Conference on Research and Innovation in Information Systems (ICRIIS)* (pp. 174-179). IEEE.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping agility through digital options: Reconceptualizing the role of information technology in contemporary firms. *MIS quarterly*, 237-263.

Sambamurthy, V., & Zmud, R. W. (1999). Arrangements for information technology governance: A theory of multiple contingencies. *MIS quarterly*, 261-290.

Sánchez, J. Á. L., Vijande, M. L. S., & Gutiérrez, J. A. T. (2010). Organisational learning and value creation in business markets. *European Journal of Marketing*.

Sanders, G. L. (1984). MIS/DSS success measure. *Systems, Objectives, Solutions*, *4*(1), 29-34.

Santos, J. R. A. (1999). Cronbach's alpha: A tool for assessing the reliability of scales. *Journal of extension*, 37(2), 1-5.

Sassen, E. J. (2009). Love, hate, or indifference: how nurses really feel about the electronic health record system. *CIN: Computers, Informatics, Nursing*, 27(5), 281-287.

Schmitt, K. F., & Wofford, D. A. (2002). Financial analysis projects clear returns from Electronic Medical Records: Demonstrating the economic benefits of an electronic medical record is possible with the input of staff who can identify the technology's benefits. *Healthcare Financial Management*, *56*(1), 52-58.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *Journal of Educational Research*, *99*(6), 323-338.

Schumacker, R. E., & Lomax, R. G. (2004). *A beginner's guide to structural equation modeling*. New York, NY: Taylor & Francis Group, LLC.

Schumacker, R. & Lomax, R. (2010). *A beginner's guide to structural equation modeling* (3rd ed.). New York, NY: Routledge.

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).

Seeman, E., & Gibson, S. (2009). Predicting acceptance of electronic medical records: is the technology acceptance model enough?. *SAM Advanced Management Journal*, *74*(4), 21-27.

Selecting the Right EMR Vendor [PDF File]. (2006). Retrieved from http://www.himss.org/files/HIMSSorg/content/files/selectingemr_flyer2.pdf

Serova, E., & Guryeva, I. (2018, October). Health Care Information Technologies Innovation. In *ECMLG 2018 14th European Conference on Management, Leadership and Governance* (p. 245). Academic Conferences and publishing limited.

Sharma, S., Daniel, E. M., & Gray, C. (2012). Absorptive capacity and ERP implementation in Indian medium-sized firms. *Journal of Global Information Management (JGIM), 20*(4), 54-79.

Sheikhy, A., & Hamzeie, A. (2015). The relationship between total quality management and Supply chain development of automotive companies listed in Tehran stock exchange. *Advances in Environmental Biology*, 9(2), 334-342.

Shi, D., Lee, T., & Maydeu-Olivares, A. (2019). Understanding the model size effect on SEM fit indices. *Educational and psychological measurement*, 79(2), 310-334.

Shi, D., Song, H., & Lewis, M. D. (2017). The Impact of Partial Factorial Invariance on Cross-Group Comparisons. *Assessment*, *1*, 17.

Sidek, Y. H., & Martins, J. T. (2017). Perceived critical success factors of electronic health record system implementation in a dental clinic context: An organisational management perspective. *International journal of medical informatics*, *107*, 88-100.

Singh, R., Mathiassen, L., Stachura, M. E., & Astapova, E. V. (2011). Dynamic Capabilities in Home Health: IT-Enabled Transformation of Post-Acute Care. *Journal of the Association for Information Systems*, *12*(2).

Sinsky, C. A., & Beasley, J. W. (2013). Texting while doctoring: a patient safety hazard. *Annals of internal medicine*, 159(11), 782-783.

Slater, S. F., & Narver, J. C. (1995). Market orientation and the learning organization. *Journal of Marketing*, 59(3), 63−74.

Smith, T. M. F. (1983). On the validity of inferences from non-random samples. *Journal of the Royal Statistical Society: Series A (General)*, 146(4), 394-403.

Snedecor, G. W. (1939). Design of sampling experiments in the social sciences. *Journal of Farm Economics*, 21(4), 846-855.

Snyder-Halpern, R., & Wagner, M. C. (2000). Planning for implementation of a vendor-based clinical information system. Case study. *Computers in nursing*, 18(1), 9.

Soh, C., Kein, S.S., & Tay-Yap, J. (2000). Enterprise Resource Planning: Cultural Fit and Misfits: Is ERP a Universal Solution? *Communications of the ACM*, 43(4), 47 - 51.

Spear, S. J. (2004). Learning to lead Toyota. Harvard Business Review, 82(5), 78−86.

Standish Group International. (2015). The chaos report. *United States of America*.

Steiger, J. H. (1990). Structural model evaluation and modification: An interval estimation approach. *Multivariate behavioral research*, *25*(2), 173-180.

Steininger, K., & Stiglbauer, B. (2015). EHR acceptance among Austrian resident doctors. *Health Policy and Technology*, *4*(2), 121-130.

Steininger, K., Stiglbauer, B., Baumgartner, B., & Engleder, B. (2014, January). Factors explaining physicians' acceptance of electronic health records. In *2014 47th Hawaii international conference on system sciences* (pp. 2768-2777). IEEE.

Stoller, J. K. (2013). Electronic siloing: An unintended consequence of the electronic health record. *Cleve Clin J Med*, 80(7), 406-9.

Streiner, D. L. (2005). Finding our way: An introduction to path analysis. *The Canadian Journal of Psychiatry*, *50*(2), 115-122. doi:10.1177/070674370505000207

Strong, D. M., & Volkoff, O. (2010). Understanding organization-enterprise system fit: a path to theorizing the information technology artifact. *MIS Quarterly*, 34(4), 731–756.

Strudwick, G., & McGillis Hall, L. (2015). Nurse acceptance of electronic health record technology: a literature review. *Journal of Research in Nursing*, *20*(7), 596-607.

Sun, P. Y., & Anderson, M. H. (2010). An examination of the relationship between absorptive capacity and organizational learning, and a proposed integration. *International Journal of Management Reviews*, *12*(2), 130-150.

Sundbo, J. (2001). The strategic management of innovation: A sociological and economic theory. Cheltenham UK: Edward Elgar.

Sung, H., Jeong, D., Jeong, Y. S., & Shin, J. I. (2015). The relationship among self-efficacy, social influence, performance expectancy, effort expectancy, and behavioral intention in mobile learning service. *International Journal of u-and e-Service, Science and Technology*, *8*(9), 197-206.

Svahn, F., Mathiassen, L., & Lindgren, R. (2017). Embracing Digital Innovation in Incumbent Firms: How Volvo Cars Managed Competing Concerns. *MIS Quarterly*, 41(1).

Talukder, M. S., Chiong, R., Bao, Y., & Hayat Malik, B. (2019). Acceptance and use predictors of fitness wearable technology and intention to recommend: An empirical study. *Industrial Management & Data Systems*, *119*(1), 170-188.

Tansel, A. U. (2013). Innovation through patient health records. *Procedia-Social and Behavioral Sciences*, 75, 183-188.

Tarka, P. (2018). An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Quality & quantity*, 52(1), 313-354.

Tavares, J., Goulão, A., & Oliveira, T. (2018). Electronic health record portals adoption: empirical model based on UTAUT2. *Informatics for Health and Social Care*, *43*(2), 109-125.

Tavares, J., & Oliveira, T. (2016). Electronic health record patient portal adoption by health care consumers: an acceptance model and survey. *Journal of medical Internet research*, *18*(3).

Teece, D. and Pisano, G. (1994). The dynamic capabilities of firms: an introduction. *Industrial and Corporate Change*, 3, 537–556.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management *Strategic management journal*, *18*(7), 509-533.

Thakkar, M., & Davis, D. C. (2006). Risks, barriers, and benefits of EHR systems: a comparative study based on size of hospital. *Perspectives in Health Information Management/AHIMA, American Health Information Management* Association, 3.

The AHIMA Foundation. (n.d.). Retrieved from http://www.ahimafoundation.org

Thompson, T. G., & Brailer, D. J. (2004). The decade of health information technology: delivering consumer-centric and information-rich health care. *Washington, DC: US Department of Health and Human Services*.

Tierney, W. M., Miller, M. E., Overhage, J. M., & McDonald, C. J. (1993). Physician inpatient order writing on microcomputer workstations: effects on resource utilization. *Jama*, 269(3), 379-383.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Research commentary—Digital infrastructures: The missing IS research agenda. *Information systems research*, *21*(4), 748-759.

Tiwana, A., Konsynski, B., & Bush, A. A. (2010). Platform evolution: coevolution of platform architecture, governance, and environmental dynamics (research commentary). *Information Systems Research*, *21*(4), 675-687.

Toivonen, M., & Tuominen, T. (2009). Emergence of innovations in services. *The Service Industries Journal*, 29(7), 887-902.

Tongco, M. D. C. (2007). Purposive sampling as a tool for informant selection. *Ethnobotany Research and applications*, *5*, 147-158.

Topp, L., Barker, B., & Degenhardt, L. (2004). The external validity of results derived from ecstasy users recruited using purposive sampling strategies. *Drug and alcohol dependence*, 73(1), 33-40.

Tornatzky, L. G., & Klein, K. J. (1982). Innovation characteristics and innovation adoption-implementation: A meta-analysis of findings. *IEEE Transactions on engineering management*, (1), 28-45.

Tripsas, M. (2009). Technology, identity, and inertia through the lens of "The Digital Photography Company". *Organization science*, *20*(2), 441-460.

Trochim, W. M., & Donnelly, J. P. (2001). *Research methods knowledge base* (Vol. 2). Cincinnati, OH: Atomic Dog Publishing.

Tseng, C. Y., Chang Pai, D., & Hung, C. H. (2011). Knowledge absorptive capacity and innovation performance in KIBS. *Journal of Knowledge Management*, *15*(6), 971-983.

Tubaishat, A. (2018). Perceived usefulness and perceived ease of use of electronic health records among nurses: application of technology acceptance model. *Informatics for Health and Social Care*, *43*(4), 379-389.

Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, *38*(1), 1-10.

Tucker, A. L., Nembhard, I. M., & Edmondson, A. C. (2007). Implementing new practices: An empirical study of organizational learning in hospital intensive care units. *Management science*, *53*(6), 894-907.

Turchetti, G., & Geisler, E. (2013). Home healthcare services: an educative case for the development of a "service-dominant logic" approach in the marketing of high-tech services. In *New Business Models and Value Creation: A Service Science Perspective* (pp. 177-191). Springer, Milano.

Uğurlu, Ö. Y., & Kurt, M. (2016). The impact of organizational learning capability on product innovation performance: Evidence from the Turkish manufacturing sector. *EMAJ: Emerging Markets Journal*, *6*(1), 70-84.

Ullman, J. B., & Bentler, P. M. (2003). *Structural equation modeling*. New York, NY: John Wiley & Sons, Inc.

Unni, P., Staes, C., Weeks, H., Kramer, H., Borbolla, D., Slager, S., ... & Weir, C. (2016). Why aren't they happy? An analysis of end-user satisfaction with Electronic health records. In *AMIA Annual Symposium Proceedings* (Vol. 2016, p. 2026). American Medical Informatics Association.

US Department of Health and Human Services. (2008). The National Alliance for Health Information Technology report to the Office of the National Coordinator for Health Information Technology on Defining Key Health Information Technology Terms.

U.S. Health Care Spending Highest Among Developed Countries. (2019, January 08). Bloomberg School of Public Health. Retrieved from https://www.jhsph.edu/news/newsreleases/2019/us-health-care-spending-highest-among-developed-countries.html

Van der Lei, J. & Talmon, J.L. (1997) Clinical decision support systems. *Handbook of Medical Informatics*, Springer, New York.

Van Slyke, C., Belanger, F., & Comunale, C. L. (2004). Factors influencing the adoption of web-based shopping: the impact of trust. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, *35*(2), 32-49.

Van Slyke, C., Lou, H., & Day, J. (2002). The impact of perceived innovation characteristics on intention to use groupware. *Information Resources Management Journal (IRMJ)*, *15*(1), 1-12.

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of marketing*, *68*(1), 1-17.

Vasilenko, D., & Khazieva, N. (2016). 4th International Conference on Management, Leadership and Governance.

Venkatesh, V., Davis, F., & Morris, M. G. (2007). Dead or alive? The development, trajectory and future of technology adoption research. *Journal of the association for information systems*, *8*(4), 1.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Venkatesh, V., Zhang, X., & Sykes, T. A. (2011). “Doctors do too little technology”: A longitudinal field study of an electronic healthcare system implementation. *Information Systems Research*, *22*(3), 523-546.

Venugopala, P., Jinkab, S., & Priyac, S. A. (2016). User acceptance of electronic health records: Cross validation of UTAUT model. *Global Management Review*, *10*(3), 42-54.

Vera, D., Crossan, M., & Apaydin, M. (2011). A framework for integrating organizational learning, knowledge, capabilities, and absorptive capacity. *Handbook of organizational learning and knowledge management*, *2*, 153-180.

Villapol, M. E., Richter, S., & Petrova, K. (2018). VALUE CO-CREATION AND OPPORTUNITIES IN HEALTH CARE AND WELLBEING: THE CASE OF THE GREEN PRESCRIPTION.

Virapongse, A., Bates, D. W., Shi, P., Jenter, C. A., Volk, L. A., Kleinman, K., ... & Simon, S. R. (2008). Electronic health records and malpractice claims in office practice. *Archives of internal medicine*, 168(21), 2362-2367.

Vitari, C., & Ologeanu-Taddei, R. (2018). The intention to use an electronic health record and its antecedents among three different categories of clinical staff. *BMC health services research*, *18*(1), 194.

Volkoff, O., Strong, D.M., & Elmes, M.B. (2007). *Technological Embeddedness and Organizational Change*. Organization Science, 18, 832-848.

Vrakking, W. J. (1995). The implementation game. *Journal of Organizational Change Management*, 8(3), 31-46.

Wager, K. A., Lee, F. W., & Glaser, J. P. (2009). Health care information systems: a practical approach for health care management.

Wah Yap, B., Ramayah, T., & Nushazelin Wan Shahidan, W. (2012). Satisfaction and trust on customer loyalty: a PLS approach. *Business Strategy Series*, 13(4), 154-167.

Wang, X. (2013). Forming mechanisms and structures of a knowledge transfer network: theoretical and simulation research. *Journal of Knowledge Management*, *17*(2), 278-289.

Wang, C. L., & Ahmed, P. K. (2003). Organisational learning: a critical review. *The learning organization*, *10*(1), 8-17.

Wang, C.L. and Ahmed, P.K. (2007). Dynamic capabilities: a review and research agenda. *International Journal of Management Reviews*, 9, pp. 31–51.

Wang, S. J., Middleton, B., Prosser, L. A., Bardon, C. G., Spurr, C. D., Carchidi, P. J., ... & Kuperman, G. J. (2003). A cost-benefit analysis of electronic medical records in primary care. *The American journal of medicine*, *114*(5), 397-403.

Wang, J., & Wang, X. (2012). *Structural equation modeling: Applications using Mplus*. Chichester: United Kingdom.

Ward, R. (2013). The application of technology acceptance and diffusion of innovation models in healthcare informatics. *health Policy and Technology*, *2*(4), 222-228.

Wass, S., & Vimarlund, V. (2016). Healthcare in the age of open innovation–A literature review. *Health Information Management Journal*, 45(3), 121-133.

Wass, S., Vimarlund, V., & Ros, A. (2017). Exploring patients' perceptions of accessing electronic health records: Innovation in healthcare. *Health informatics journal*, 1460458217704258.

Weiskopf, N. G., & Weng, C. (2013). Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *Journal of the American Medical Informatics Association*, *20*(1), 144-151.

Welcome to mHealth Knowledge. www.mhealthknowledge.org. (n.d.). Retrieved from http://www.mhealthalliance.org/

Westbrook, J. I., Braithwaite, J., Georgiou, A., Ampt, A., Creswick, N., Coiera, E., & Iedema, R. (2007). Multimethod evaluation of information and communication technologies in health in the context of wicked problems and sociotechnical theory. *Journal of the American Medical Informatics Association*, *14*(6), 746-755.

Weston, R., & Gore, P. A., Jr. (2006). SEM 101: A brief guide to structural equation modeling. *The Counseling Psychologist*, *34*, 719-751.

What are the advantages of electronic health records? (n.d.). Retrieved from https://www.healthit.gov/faq/what-are-advantages-electronic-health-records

Wheaton, B., Muthén, B., Alwin, D. F., & Summers, G. F. (1977). Assessing reliability and stability in panel models. *Sociological methodology*, *8*, 84-136.

Wheeler, B. C. (2002). NEBIC: A dynamic capabilities theory for assessing net-enablement. *Information systems research*, *13*(2), 125-146.

Wilden, R., & Gudergan, S. (2017). Service-dominant orientation, dynamic capabilities and firm performance. *Journal of Service Theory and Practice*, *27*(4), 808-832.

Wilkins, M. A. (2009). Factors influencing acceptance of electronic health records in hospitals. *Perspectives in Health Information Management/AHIMA, American Health Information Management Association*, *6*(Fall).

Williams, B. (1990). How to do an ROI (return on investment). *Healthcare informatics: the business magazine for information and communication systems*, *7*(2), 30-32.

Williams, B., Onsman, A., & Brown, T. (2010). Exploratory factor analysis: A five-step guide for novices. *Australasian Journal of Paramedicine*, *8*(3).

Williams, M., Rana, N., Dwivedi, Y., & Lal, B. (2011). Is UTAUT really used or just cited for the sake of it? A systematic review of citations of UTAUT's originating article.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): a literature review. *Journal of enterprise information management*.

Willson, D., Ashton, C., Wingate, N., Goff, C., Horn, S., Davies, M., & Buxton, R. (1995). Computerized support of pressure ulcer prevention and treatment protocols. In Proceedings of the Annual Symposium on Computer Application in Medical Care (p.646). *American Medical Informatics Association*.

Wilson, J. C. (2018). *Testing an Integrated Health Promotion Model Using Social Media for Breastfeeding Women: Structural Equation Modeling* (Doctoral dissertation, Florida Atlantic University).

Wilson, G. A., McDonald, C. J., & McCabe Jr, G. P. (1982). The effect of immediate access to a computerized medical record on physician test ordering: a controlled clinical trial in the emergency room. *American Journal of Public Health*, 72(7), 698-702.

Winter, S. G. (2000). The satisficing principle in capability learning. *Strategic management journal*, *21*(10-11), 981-996.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic management journal*, *24*(10), 991-995.

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models. *Educational and Psychological Measurement, 73*(6), 913-934. doi:10.1177/0013164413495237

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices, *The Counseling Psychologies*, 34(6), 806-838.

Wright, A., Soran, C., Jenter, C. A., Volk, L. A., Bates, D. W., & Simon, S. R. (2010). Physician attitudes toward health information exchange: results of a statewide survey. *Journal of the American Medical Informatics Association*, *17*(1), 66-70.

Wu, P. Y., Cheng, C. W., Kaddi, C. D., Venugopalan, J., Hoffman, R., & Wang, M. D. (2016). –Omic and electronic health record big data analytics for precision medicine. *IEEE Transactions on Biomedical Engineering*, 64(2), 263-273.

Wu, L., Li, J. Y., & Fu, C. Y. (2011). The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision support systems, 51*(3), 587-596.

Wu, J. H., Shen, W. S., Lin, L. M., Greenes, R. A., & Bates, D. W. (2008). Testing the technology acceptance model for evaluating healthcare professionals' intention to use an adverse event reporting system. *International Journal for Quality in Health Care*, *20*(2), 123-129.

Wu, J. H., Wang, S. C., & Lin, L. M. (2007). Mobile computing acceptance factors in the healthcare industry: A structural equation model. *International journal of medical informatics*, *76*(1), 66-77.

Wu, Y., Wang, Y., Song, J., & Byrd, T. (2015, March). The Impact of Knowledge from Learning-About Electronic Health Records on it Innovation Adoption: The Moderating Role of Absorptive Capacity. In *Proceeding of the Southern Association for Information Systems Conference, Hilton Head Island, SC, USA*.

Xie, X., Zou, H., & Qi, G. (2018). Knowledge absorptive capacity and innovation performance in high-tech companies: A multi-mediating analysis. *Journal of Business Research*, *88*, 289-297.

Yan, Y., Chung, K. (2016). Doctor-patient relationship and value co-creation: An empirical study of service-dominant logic. *Journal of Nursing & Care*.

Yan, J., Ye, K., Wang, H., & Hua, Z. (2010). Ontology of collaborative manufacturing: Alignment of service-oriented framework with service-dominant logic. *Expert Systems with Applications*, *37*(3), 2222-2231.

Yen, P. Y., McAlearney, A. S., Sieck, C. J., Hefner, J. L., & Huerta, T. R. (2017). Health information technology (HIT) adaptation: refocusing on the journey to successful HIT implementation. *JMIR medical informatics*, *5*(3).

Yeo, K. T. (2002). Critical failure factors in information system projects. *International journal of project management*, *20*(3), 241-246.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). Research commentary—the new organizing logic of digital innovation: an agenda for information systems research. *Information systems research*, *21*(4), 724-735.

Yu, P., & Qian, S. (2018). Developing a theoretical model and questionnaire survey instrument to measure the success of electronic health records in residential aged care. *PloS one*, *13*(1), e0190749.

Zahra, S. A., & George, G. (2002). Absorptive capacity: A review, reconceptualization, and extension. *Academy of management review*, *27*(2), 185-203.

Zahra, S. A., Sapienza, H. J., & Davidsson, P. (2006). Entrepreneurship and dynamic capabilities: A review, model and research agenda. *Journal of Management studies*, *43*(4), 917-955.

Zaltman, G., Duncan, R.& Holbek, J. (1973), Innovations and Organizations, Wiley, New York, NY.

Zandieh, S. O., Yoon-Flannery, K., Kuperman, G. J., Langsam, D. J., Hyman, D., & Kaushal, R (2008). Challenges to EHR implementation in electronic-versus paper-based office practices. *Journal of general internal medicine*, *23*(6), 755-761.

Zaroukian, M. H., & Sierra, A. (2006). Benefiting from ambulatory EHR implementation: solidarity, six sigma, and willingness to strive. *Journal of Healthcare Information Management*, 20(1), 53.

Zhang, Z. (2017). Structural equation modeling in the context of clinical research. *Annals of translational medicine*, 5(5).

Zhang, L., Tong, H., Demirel, H. O., Duffy, V. G., Yih, Y., & Bidassie, B. (2015). A practical model of value co-creation in healthcare service. *Procedia Manufacturing*, *3*, 200-207.

Zhang, J., & Walji, M. F. (2011). TURF: toward a unified framework of EHR usability. *Journal of biomedical informatics*, 44(6), 1056-1067.

Zhang, Y., Yu, P., & Shen, J. (2012). The benefits of introducing electronic health records in residential aged care facilities: a multiple case study. *International journal of medical informatics*, 81(10), 690-704.

Zlabek, J. A., Wickus, J. W., & Mathiason, M. A. (2011). Early cost and safety benefits of an inpatient electronic health record. *Journal of the American Medical Informatics Association*, 18(2), 169-172.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization science*, *13*(3), 339-351.

APPENDIX A: INSTRUMENT CONSTRUCTS, ITEMS, SOURCE(S)

Serial Number	Original Text	Modified Text	Source
t1	My interaction with EHR will be user-friendly	I find EHR to be user-friendly	Morton and Wiedenbeck (2009)
t3	I expect to become skilled using EHR	It is possible to become skilled at using EHR	Morton and Wiedenbeck (2009)
t7	Using the system increases my productivity	Using EHR increases productivity	Venkatesh, Morris, Davis and Davis (2003)
t10	The results of using a PWS are apparent to me	The results of using EHR are apparent to me	Moore and Benbasat (1991)
o14	When we do not have the necessary specific knowledge we look for it and acquire it outside the organization.	The organization looks for and acquires any necessary and/or specific knowledge it lacks from outside the organization	Sánchez, Vijande, and Gutiérrez (2010)
o15	We use formal and reiterative procedures to evaluate our results (and compare them with those of the competion)	Formal and reiterative procedures are used to evaluate results	Sánchez, Vijande, and Gutiérrez (2010)
o17	There is an atmosphere of trust and collaboration among the personnel of the company leading to cooperationwhen an opportunity or problem that needs a solution arises	There is an atmosphere of trust and collaboration among the personnel of the organization leading to cooperation when an opportunity or problem that needs a solution arises	Sánchez, Vijande, and Gutiérrez (2010)

o18	We are successful in learning new things within this group.	The organization as a whole is successful in learning new things	Pavlou and El Sawy (2006)
o19	We are able to identify and acquire internal (e.g., within the group) and external (e.g., market) knowledge	The organization and its people are able to successfully acquire internal and external knowledge	Pavlou and El Sawy (2006)
o20	We have effective routines to identify, value, and import new information and knowledge.	There are routines to identify, value, and import new information and knowledge	Pavlou and El Sawy (2006)
o21	We have adequate routines to analyze the information and knowledge obtained	There are adequate routines to analyze the information and knowledge obtained	Pavlou and El Sawy (2006)
o22	We have adequate routines to assimilate new information and knowledge	There are adequate routines to assimilate new information and knowledge	Pavlou and El Sawy (2006)
o23	We can successfully integrate our existing knowledge with the new information and knowledge acquired.	The organization and its people are able to successfully integrate existing information into new knowledge	Pavlou and El Sawy (2006)
o24	We are effective in transforming existing information into new knowledge	Existing information is transformed into new knowledge effectively	Pavlou and El Sawy (2006)
o25	We can successfully exploit internal and external information and knowledge into concrete applications	Internal and external information and knowledge are successfully exploited into concrete applications	Pavlou and El Sawy (2006)
o26	We are effective in utilizing knowledge into new products.	Knowledge is effectively incorporated into new products or services	Pavlou and El Sawy (2006)
s27	We lead the way in introducing service innovations that require brand new competences	The organization leads in introducing radical product and service innovations (modified from Deshpande)	Chandy and Tellis (1998)

s28	We constantly consider introducing new services that satisfy future market needs	The organization constantly considers introducing new services that satisfy the healthcare receiver's needs	Chandy and Tellis (1998)
s29	Our product and service development is based on good market and customer information	The organization's product and service development is based on good market and customer information	Desphande, Farley, and Webster (1993)
s30	We have a good sense of how our customers value our products and services	There is a good sense within the organization of how customers value the organization's products and services	Desphande, Farley, and Webster (1993)
s31	We are more customer focused than our competitors	The organization is healthcare receiver focused	Desphande, Farley, and Webster (1993)
s32	We compete primarily based on product or service differentiation	The organization competes primarily on the basis of service differentiation	Desphande, Farley, and Webster (1993)
s33	We believe the customer's interest should always come first ahead of the company's interest	The organization puts healthcare receiver's best interest first	Desphande, Farley, and Webster (1993)
s35	Technical innovation, based on research results, is readily accepted	Technical innovation is readily accepted	Hurley and Hult (1998)
s36	Management actively seeks innovative ideas	Management actively seeks innovative ideas	Hurley and Hult (1998)
s37	Innovation is readily accepted in program/project management	Innovation is readily accepted in program/project management	Hurley and Hult (1998)
s38	People are penalized for new ideas that don't work	People are not penalized for new ideas that don't work	Hurley and Hult (1998)
d39	EMR is an appropriate tool for physicians to use	I believe that EHR is an appropriate tool to use to provide service to healthcare receivers	Seeman and Gibson (2009)

d41	I find EMR technology useful for my patient care and management	I believe EHR is useful for patient care and management	Seeman and Gibson (2009)
d42	Using EMR is a wise idea	Using EHR is a wise idea	Seeman and Gibson (2009)
d45	Satisfied with system	I am satisfied with the design and features of EHR	Holden, Brown, Scanlon and Karsh (2012)
d46	Would recommend to a friend at another hospital	I would have no hesitation in recommending EHR use	Holden, Brown, Scanlon and Karsh (2012)
d47	Prefer system to prior process	I believe EHR use is better compared to the process that was in place before it	Holden, Brown, Scanlon and Karsh (2012)
d48	Intend to use system, if I have access	I would use EHRs for a long time to come if am in a job where EHR use makes sense	Holden, Brown, Scanlon and Karsh (2012)
d49	Predict I will use system, if it were up to me	I predict I will use the EHR as long as I am given access	Holden, Brown, Scanlon and Karsh (2012)

APPENDIX B: IRB APPROVAL LETTER

Indiana State University
More. From day one.

Institutional Review Board

Terre Haute, Indiana 47809
812-237-3088
Fax 812-237-3092

DATE:	August 7, 2019
TO:	Anuradha Rangarajan, MS, MBA
FROM:	Indiana State University Institutional Review Board
STUDY TITLE:	[1443817-2] TECHNOLOGY ATTRIBUTES, ORGANIZATIONAL LEARNING ATTRIBUTES, SERVICE ATTRIBUTES, AND ELECTRONIC HEALTH RECORD IMPLEMENTATION SUCCESS
SUBMISSION TYPE:	Revision
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	August 7, 2019
REVIEW CATEGORY:	Exemption category # 2

Thank you for your submission of Revision materials for this research study. The Indiana State University Institutional Review Board has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations (45 CFR 46). You do not need to submit continuation requests or a completion report. Should you need to make modifications to your protocol or informed consent forms that do not fall within the exempt categories, you will have to reapply to the IRB for review of your modified study.

Internet Research: If you are using an internet platform to collect data on human subjects, although your study is exempt from IRB review, ISU has specific policies about internet research that you should follow to the best of your ability and capability. Please review Section L. on Internet Research in the IRB Policy Manual.

Informed Consent: All ISU faculty, staff, and students conducting human subjects research within the "exempt" category are still ethically bound to follow the basic ethical principles of the Belmont Report: 1) respect for persons; 2) beneficence; and 3) justice. These three principles are best reflected in the practice of obtaining informed consent.

If you have any questions, please contact Anne Foster within IRBNet by clicking on the study title on the "My Projects" screen and the "Send Project Mail" button on the left side of the "New Project Message" screen. I wish you well in completing your study.

APPENDIX C: INFORMED CONSENT

INFORMATION FOR PARTICIPATION IN RESEARCH STUDY

1. INFORMATION FOR PARTICIPATION IN RESEARCH STUDY

RESEARCH ABOUT FACTORS IMPACTING ELECTRONIC HEALTH RECORD IMPLEMENTATION SUCCESS

This is a research study concerned with uncovering factors that may have an impact on the implementation success of Electronic Health Records (EHR). Your participation in this study is entirely voluntary. There will be no negative consequences if you decide not to participate. The information provided in this section (also known as 'Informed Consent') should help you decide if you want to participate in this research study or not. The principal researcher in this study is Ms. Anuradha Rangarajan, a PhD candidate at the Indiana State University at the College of Technology. The faculty sponsor for this research study is Dr. Mehran Shahhosseini. The desired respondent profile for this study is: Information Technology (IT) & management consultants, project managers, physicians, nurses, healthcare facility administrators, healthcare facility staff such as pharmacists and physical therapists, and other medical/technology professionals who have been part of an *EHR experience (i.e. involved in the implementation/use/maintenance of EHR)* for a period equal to or greater than one year in the last five years.

If you agree to participate….

If you agree to participate, you will be asked to complete a survey in the form of a questionnaire (if you meet the conditions for the respondent profile). The desired respondent profile for this study is stated above.

Can I decide not to participate?

Participation in this research study is entirely voluntary. You may choose not to participate if you do not desire to do so. You may decline to participate after reading this informed consent, or at any time during or after the data collection by informing the principal investigator Anuradha Rangarajan verbally (if taking the paper based version of this questionnaire) or by closing and exiting the survey (if taking electronic version over the internet). You also can choose to answer or not answer any question you like. No one will know whether you participated or not.

Some reasons you might want to participate in this research are to contribute to an important research study to uncover a unique combination of attributes that have a positive association with EHR implementation success. This study aims to make a significant contribution to research literature, potentially benefit providers & patients, and, improve satisfaction among physicians, healthcare administration staff and healthcare information technology professionals. Some reasons you might not want to participate in this research can be your perceived loss of confidentiality in completing this survey, embarrassment, feels of sorrow or anger if the questions are provoking.

What is my time commitment?

The principal researcher estimates that it will take you approximately 20 minutes to complete the survey/questionnaire.

Are there any risks involved?

The only task you are required to do should you agree to participate in this study is to fill out a survey/questionnaire. Although every effort will be made to protect your answers, complete anonymity cannot be guaranteed over the Internet. Other potential risks of the study include potential *to loss of confidentiality, embarrassment, feels of sorrow or anger if the questions are provoking, etc.* Respondents who respond to the survey electronically are assured of confidentiality as the IP address of the computer they take the survey from is not stored. Respondents of the paper survey form are not required to share any form of personal identifying information (i.e.) their name

Are there any benefits to me in participating in this study?

Though there will be no personal rewards or benefits to you in participating in this study, the results from this study are expected to help the academic community and the practitioner (healthcare) community. The results may be disseminated through journals and conferences in the future. Hence you will be indirectly a part of an important research work related to healthcare process and the healthcare industry. Hence the principal researcher values the contribution of every individual that participates in the research study.

What about confidentiality- should I be concerned?

Records pertaining to this research study including responses to the questionnaire survey will be kept strictly confidential and only the principal researcher will have access to them. The only exception to this rule is access by the principal researcher's academic committee and the university's Institutional Review Board (IRB), whose interest in reviewing is only to ensure the research has been conducted in an appropriate manner. Any results will be released in aggregated format (i.e. without reference to any specific individual or organization). We will never individually identify you, the respondent. Information may be released if required by law, but note that even when such information is released, it will not contain any information identifying the respondent such as names or IP addresses.

What if I have any further questions?

If you have questions about this research study, please contact the principal researcher Ms. Anuradha Rangarajan (arangarajan@sycamores.indstate.edu) or the faculty sponsor Dr. Mehran Shahhosseini (mehran.shahhosseini@indstate.edu). You may also contact the Chair of the IRB of Indiana State University (irb@indstate.edu or (812) 237 - 3088) if you have questions about your rights as a respondent.

THE PRINCIPAL RESEARCHER THANKS YOU FOR YOUR TIME AND PARTICIPATION!