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Predictive Relationships Between Electronic Health Records Attributes and Meaningful Use Objectives

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Abstract

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MSTM, George Mason University, 2011

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

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Abstract

The use of electronic health records (EHR) has the potential to improve relationships between physicians and patients and significantly improve care delivery. The purpose of this study was to analyze the relationships between hospital attributes and EHR implementation. The research design for this study was the cross-sectional approach. Secondary data from the Health Information and Management Systems Society (HIMSS) Analytics Database was utilized ($n = 169$) in a correlational crosssectional research design. Normalization Process Theory (NPT) and implementation theory were the theoretical underpinnings used in this study. Multiple linear regressions results showed statistically significant relationships between the 4 independent variables (region, ownership status, number of staffed beds [size], and organizational control) and the outcomes for the dependent variables of EHR software application attributes (Clinical Decision Support Systems (CDSS) components), EHR software application attributes (major systems), and successful implementation of Meaningful Use (MU) ($p = .001$). A statistically significant relationship ($p = .001$) was also found between the 2 independent variables (EHR software application attributes [CDSS components] and EHR software application attributes [major systems]) and the outcome of successful implementation of MU when combined. This evidence should provide policy makers and health practitioners support for their attempts to implement EHR systems to result in positive Meaningful Use. The potential social change is improved medication prescribing and administration for hospitals and, lower cost and better quality of care for patients.

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Dedication

I dedicate this dissertation to my mother, who instilled the value of good education in my siblings and me. At age 12, in spite of her stepmother's discouragement and a lack of support from her father, she defied all odds and sat in the same class with people half her age. Her determination and tenacity have resulted in countless successes as an entrepreneur and a lineage of several physicians and successful businesspersons. Mum, you have raised giants, and your legacy will be eternal.

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Chapter 1: Introduction to the Study

Introduction

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, which was signed as part of the American Recovery and Reinvestment Act (ARRA) of 2009, has been instrumental in driving adoption of comprehensive electronic health records (EHRs) across the United States (DesRoches, Worzala, Joshi, Kralovec, & Jha, 2012). The HITECH program incentivizes hospitals to demonstrate their adoption and "meaningful use" of certified EHR systems as part of it's the mandate that most U.S. hospitals use comprehensive electronic systems by 2020 (DesRoches et al., 2012). The meaningful use criteria established by the HITECH Act includes specific guidelines to incentivize qualified health care providers, facilities, and critical access hospitals (CAHs) to employ EHRs to accomplish their intended objectives (Kennedy, Murphy, & Roberts, 2013).

Meaningful use (MU) involves employing EHR technology which is certified by the Centers for Medicare and Medicaid Services (CMS) to improve quality, safety, and efficiency and reduce health disparities (CMS, 2016b). It encompasses partnering with patients and families in their health care, improving care coordination, enhancing population and public health, and preserving the privacy and security of all participants (CMS, 2016b). The demonstration of MU has a significant impact on care delivery to Medicare and Medicaid patients, as illustrated by the U.S. government's support of the use of EHRs for upgrading delivery of care and public health (Shea, Reiter, Weaver, Thornhill, & Malone, 2015).

A number of researchers who have studied the adoption of EHRs have raised concerns about the quality of the data contained in them after implementation (see Callen, 2014; Haghighi, Dehghani, Teshizi, & Mahmoodi, 2013; Harteloh, De Bruin, & Kardaun 2010; Paul & Robinson, 2012). Concerns include mediocre recording and tracking of drug allergy in the medical information of patients, inadequate reporting of harmful drug reactions, partial coding, and erroneous coding for cause of death which resulted in documentation errors in death certificates (Haghighi et al., 2013; Paul & Robinson, 2012). The importance of the demonstration of MU underscores the need to investigate how providers demonstrate MU. This can be done by focusing on the relationship between EHR software application attributes implemented, and hospital demographics to measure Stage 1 MU objectives (Shea et al., 2015). The purpose of this study was to evaluate how hospital characteristics and EHR software attributes influence the MU implementation process for the demonstration of Stage 1 MU objectives. These following sections include the study's variables, research design and rationale, methodology, validity threats including ethical concerns, and summary.

Background

EHRs have the potential to enhance interactions between physicians and patients and improve the quality, safety, and efficiency of care delivery (Weiner, Fowles, & Chan, 2012). EHRs have become an important topic in health care and have emerged as the focus of the federal government's approach for improving healthcare the quality, safety and delivery in the United States. ARRA, which was passed in February 2009, gave rise to the HITECH Act. The main objective of the HITECH Act is to promote meaningful use of certified EHR technology (DesRoches et al., 2012). It authorized the establishment of an incentive payment program for eligible professionals (e.g., physicians) and eligible hospitals that achieve "meaningful use" of qualified EHRs and interoperable health information technology (CMS, 2016b). To define and to implement this incentive program, the CMS issued a Final Rule entitled Medicare and Medicaid Programs; Electronic Health Record Incentive Program in 2010 (42 CFR Parts 412, 413, 422, et al.; CMS, 2010). The HITECH Act also required the Secretary of Health and Human Services (HHS) to adopt an initial set of standards, implementation specifications, and certification criteria for EHRs, as well as establish a certification program for EHRs (HITECH Act Enforcement Interim Final Rule, 2009).

Legally, meaningful use is achieved by using certified EHR technology that complies with predetermined functional and technical criteria (CMS, 2016b). In this study, I measured the predictive relationships between EHR attributes and MU objectives. I used normalization process theory (NPT), (May, & Finch, 2009) and implementation theory (May, 2013A) as the theoretical framework to address my two research questions. I could not locate any study on MU in which these theories served as the theoretical framework for answering the research questions; thus, I believe that this study filled a knowledge gap in the discipline.

Problem Statement

I designed this study to investigate the extent to which EHR software application attributes influence the successful implementation of Stage 1 MU objectives for critical access hospitals (CAHs), a designation created by Congress in the 1997 Balanced Budget

Act for certain rural hospitals (Health Resources & Service Administration, n.d.). Researchers who have studied the adoption of EHRs have expressed quality concerns regarding inaccurate or incomplete coding and processing of drug allergy data and other medication data for patients after implementation of EHRs (Haghighi et al., 2013; Paul & Robinson, 2012). The demonstration of MU can impact the type of care received by Medicare and Medicaid patients (Shea et al., 2015). Although research regarding the implementation of EHRs has illuminated important findings (House & Mishra, 2015), I did not find any research on the relationship between EHR software application attributes and successful implementation of MU objectives in critical access hospitals. Given this gap in the literature, I concluded that further research was warranted to address the documented problem of the negative effects on patient care of inefficient and ineffective implementation of EHRs.

Purpose of the Study

In this study, I analyzed the relationship between EHR attributes and their relationship to the Stage 1 MU implementation process. To the extent that MU affects care delivery, demonstration of MU may have an impact on the government's evaluation of the care offered to Medicare and Medicaid patients (Shea, Reiter, Weaver, Thornhill, & Malone, 2015). In light of the renewed efforts by the U.S. government to encourage the use of EHRs for upgrading delivery of care and public health, it is necessary to analyze the circumstances that impact how providers demonstrate MU by focusing on EHR software application attributes and hospital demographics to measure Stage 1 MU objectives (Shea et al., 2015). The aim of this study was to produce insight about the relationships between hospital attributes and EHR implementation, which may help policy makers, health systems, and practice leaders tailor policies and allocate resources effectively as well as support providers in practice settings who may otherwise not able to demonstrate MU.

The independent variables included hospital facility type, organizational control, ownership status, profit status, location/region, and size. I used these variables to determine the relationship between the characteristics of hospitals and EHR software application attributes, and whether those relationships affected hospitals' attestation of MU. There were two dependent variables for this study. The first dependent variable was EHR software application attributes which consisted of Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status. The second dependent variable for this study was the implementation of Stage 1 MU. This variable consisted of CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information. This variable was used to determine the extent to which hospital demographics and the characteristics of the EHR software application can influence the attainment of MU objectives.

Research Question and Hypotheses

RQ 1 – What is the predictive relationship between hospital attributes (facility type, organizational control, ownership status, profit status, location/ region, and size) and

EHR software application attributes implemented? (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status?

Null Hypothesis 1 ($H_0 1$): There is no statistically predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status.

Alternative Hypothesis 1 ($H_A 1$): There is a statistically significant predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status.

RQ 2 – What is the predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status and successful implementation of Stage 1 MU objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information)?

Null Hypothesis 2 ($H_0 2$): There is no statistically significant predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - Electronic Forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE status and successful implementation of Stage 1 Meaningful Use (MU) objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Alternative Hypothesis 2 ($H_A 2$): There is a statistically significant predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE status and successful implementation of Stage 1 MU objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Theoretical Framework

The theoretical framework for this study consisted of NPT (May, & Finch, 2009) and implementation theory (May, 2013).

Normalization Process Theory (NPT)

As a theory, NPT is a social process of communal action. It provides a consistent framework for identifying factors that stimulate and impede the standard integration of complex interventions into normal practice by offering researchers a basis for representing varied contexts, structures, social norms, group processes and conventions (Murray et al., 2010). NPT focuses on what work needs to be done, by whom, how it is done, and the benefits and costs of the work that is done (May, 2013a).

Implementations occur within socially organized, evolving linkages called social systems. Implementations are also are populated by agents who operate within social structures or contexts that provide social roles and norms (Bunge, 2004; May, 2013a). Agents or actors are individuals and organizations that work together in health care settings and include health professionals, hospital managers, and patients (Bunge, 2004; May, 2013a). Implementations involving technological, behavioral, and organizational processes are prominent in health care practice; however, the relationships between their components are unpredictable to evaluate (Campbell et al., 2007). Researchers have focused on the clinical and cost effectiveness of complex interventions in the case of trials and other outcomes studies while process evaluations explain the steps involved in arriving at results and the components that facilitate or impede those outcomes (Campbell et al., 2007). Consequently, process evaluations have become a key focus for health services researchers (May, 2006; May et al., 2007b; May, Mair, Dowrick, & Finch, 2007a).

Propositions & constructs. The three major components of NPT include implementing work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009). The first of the three propositions of NPT states that complex interventions involve exchanges within a particular situation over time, during which time individuals and groups implement practices in social contexts within which they become routinely embedded (May & Finch, 2009). The second proposition affirms that implementation processes is comprise of four constructs (coherence, cognitive participation, collective action, and reflexive monitoring), which are influenced by elements that enhance or hinder inserting a practice in its social contexts (May & Finch, 2009). The third proposition involves the requirement for an uninterrupted action by individuals or groups in a complex intervention (May & Finch, 2009). Based on these propositions, it can be argued that NPT offers important perspectives into how new or modified work processes can be routinized in their respective social systems.

Coherence or sense-making. The coherence or sense-making construct addresses how actors specify their involvement in a practice (May, 2013a; May et al., 2007a). It also involves how embedding is influenced by elements that foster or obstruct the concerns of actors about the essence of the actions that people perform to meet specific goals (May & Finch, 2009). For an intervention to be successfully routinized, there must be shared knowledge by the actors (May, 2013a; May et al., 2007a).

Cognitive participation. Cognitive participation involves actors who are members of an identifiable practice group. It also involves an explanation of how membership is obtained. Embedding or normalizing is predicated on the actors involved in a procedure and by elements that foster or obstruct the involvement of the actors (May, 2013a; May et al., 2007a).

Collective action. Collective action entails the performance of actors in a complex intervention. Embedding is influenced by elements that foster or obstruct the ability of actors authorizing it, by work that describes and operationalizes a procedure, and by the communal effort of participants in it (May, 2013A; May et al., 2007A).

Reflexive monitoring. Reflexive monitoring describes information processing of the outcomes of the intervention. Embedding relies on work that explains and organizes a regular routine (May, 2013A; May et al., 2007A).

NPT was developed by researchers who focused on understanding the implementation of advanced and complicated interventions in healthcare settings (McEvoy et al., 2014; May et al., 2007B). NPT does not address the relationships between individual attitudes and behaviors but focuses on the treatment of knowledge across professional groups, and aims to understand the implementation of new knowledge by healthcare professionals (Murray, Burns, May, Finch, O'Donnell, Wallace, & Mair, 2011; Gallacher, May, Montori & Mair, 2011). It is analogous to theories of actor networks and diffusion of innovation (Galusky, 2008; Rogers, 1995) because it addresses the authenticity of the intervention and the function of opinion leaders. It is also concerned with understanding trust and connections within social networks in the context of new ideas (Harris, Provan, Johnson & Leischow, 2012; Doumit, Wright, Graham, Smith & Grimshaw, 2011).

Context & agency. Contexts are the physical, organizational, institutional and legislative frameworks that support or hinder resources, people and procedures (May et al., 2007). They can also be described as the infrastructure within social norms, rules and roles are enforced. The potential construct and the capacity construct emphasize contextual elements. Agency explains the actions and decisions that individuals and groups make when constrained by conditions and contingencies in the course of an implementation (May, 2013A). Agency influences proactive engagement by the individual or group in their development, improvement and adaptation over time (Bandura, 2001). The capability construct and the contribution construct highlight agency (May, 2013A; May et al., 2007A). Context and agency embody the four constructs of the implementation theory and provide a more streamlined approach to explain the key components of a complex intervention.

Implementation Theory

Implementation theory provides a structure for investigating implementation of complicated interventions and a way to measure and analyze progress and results. This framework originated from NPT and includes the implementation of work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009). It also explains implanting and incorporation of new ideas into healthcare settings and draws attention of researchers to potential challenges during the implementation of services (May 2006); Morrison & Mair, 2012;

Murray et al., 2010). A complex intervention refers to organizing new or modified work while embedding involves standardizing or normalizing work, and integration refers to the process of making practices part of their social contexts (May & Finch, 2009; May, Mair, Finch, MacFarlane, Dowrick, Treweek, Rapley, Ballini, Ong, Rogers, et al., 2009). A complex intervention impacts both the individual and shared knowledge and the extent to which participants hold each other accountable (May & Finch, 2009; May et al., 2009; May 2013A; May et al., 2007A).

Constructs of theory. Implementation theory provides four constructs that help experts to identify and describe the components of implementations and their results (May, 2013A). The four constructs of implementation theory are capacity, potential, capability, and contribution which are at the core of the theory and are integrated to provide thorough explanations for the processes by which complicated interventions are inserted into health procedures (May & Finch, 2009; May et al., 2009; May, May et al., 2007A).

Capacity. The capacity construct focuses on the social systems within which implementations occur (May, 2013A). It describes social networks as important precursors for implementations because they provide contexts for relationships and information flow during the implementation of a complex intervention. These contexts, or social structural resources, include social norms or rules, roles, material and cognitive resources that govern the work that is done (May, 2013A). The theoretical basis for the capacity construct is the Strategic Action Field Theory (Fligstein & McAdam, 2011), which postulates that strategic action fields (SAFs) are the basic elements of communal action in society. It is comprised of actors with knowledge of one another, relationships, power distributions and rules. Organizations, extended families, social movements, and governmental systems are themselves made up of SAFs. The basic premise of the capacity construct is that the level of cooperation and collaboration that takes place in the course of a complex intervention is affected by the social roles, norms that regulate their conduct, and the material and information resources that available within that social structure (May, 2013A). In the context of this study, the capacity construct describes the attributes of the hospital as a social system within which EHR implementations occur.

Potential. The potential construct focuses on an individual agent's willingness to conform to social norms, roles and rules within a social system and highlights the value that stakeholders assign to new ideas, their attitudes, shared values and commitment (May, 2013A; May et al., 2007A). The basic premise of the potential construct is that an individual or group is able to achieve their goal of implementing a complex intervention only if they are willing or prepared to do so. Their willingness to implement the complex intervention is also driven by their experience and capability to complete their task (May, 2013A; May et al., 2007A).

Organizational readiness for change is a vital precondition for the successful implementation of new ideas in healthcare setups (Armenakis, Harris, & Mossholder, 1993; Hardison, 1998). It can be determined at the individual, group, or organizational level and it emphasizes shared resolve. Organizational changes such as EHRs, quality improvement programs and patient safety systems in healthcare delivery all require collective effort by constituents (Weiner, 2009). Purposeful individual intentions and the shared commitment towards the completion of tasks is important. In the context of this study, the potential construct describes the decisions and actions of healthcare practitioners and the hospital as an organizational unit during complex interventions such as EHR implementations.

Capability. The capability construct is drawn from the theory of normalization process and postulates that the capability of agents determines the extent to which new ideas or processes can be implemented to produce new opportunities (May, 2013a; Murray et al., 2010). The capability construct focuses on what is being implemented and describes the object of an implementation as a complex intervention (May, 2013a; Murray et al., 2010). When agents perform complex interventions, they employ multiple relations, interactions, techniques and technologies or organizational systems (May, 2013a; Murray et al., 2010).

The attributes of the components of a complex intervention – physical or virtual character, type of use, agent, and level of complexity – impact how they are used. The extent to which the qualities of a complex intervention can be incorporated into existing procedures is a crucial element of an implementation process (May, 2013A; Murray et al., 2010). Workability involves the interactions between users and the elements of a complex intervention; integration involves interactions between the circumstances of use and the elements of a complex intervention (May, 2013A; Murray et al., 2010). In the context of this study the capability construct describes the extent to which EHR implementation can be implemented in a hospital to produce new opportunities in the form of higher operational efficiencies, lower costs and improved patient safety (May, 2013A; Murray et al., 2010).

Contribution. Contribution addresses ongoing support from stakeholders as a key success factor in the implementation of new ideas (May, 2013A; Murray et al., 2010). Agents are part of social systems that are formed when social roles and norms are established through organized and evolving relations which promote information flows within the resulting social structures (May, 2013A; Murray et al., 2010). The social structures enable the formation and expression of individual intentions and collective commitments which lead to the completion of complex interventions (May, 2013A; Murray et al., 2010). In the context of this study the contribution construct provides a framework for locating agentic intentions during MU interventions.

Integration of capacity, potential, capability, & contribution. The combination of the capacity, potential, capability and contribution constructs illustrate the dynamics of a complex intervention and the alignment between the various components. The capacity construct provides the framework for transmission of information and interactions between individuals and groups, which are regulated by social norms or rules, roles, as well as physical and intellectual resources (May, 2013A). The potential construct provides the actors whose willingness and ability to operate within the established social norms, roles and rules of the framework are evidenced by their attitudes, shared values and commitment to the complex intervention (May, 2013A; May et al., 2007A). The capability construct determines the extent to which new ideas or processes can be successfully implemented by the actors in a social network to produce the desired outcome of an implementation (May, 2013; Murray et al., 2010). The contribution construct addresses the sustainability of the complex intervention which is determined by continued support from all constituents of a complex intervention (May, 2013A; Murray et al., 2010). The interactions between the constructs do not always occur in the same order because they integrative. Each of the above components is important and must be functional within the right context to assure the success of a complex intervention.

NPT and implementation theory were chosen for this study because they offered a way to identify and explain the dynamics between agentic expressions and different contexts within a complex intervention and provided a robust theoretical framework for addressing both individual and organizational level factors (Murray et al., 2010). The constructs of these theories were also germane to the key components of this study and, provided a firm basis for answering the research questions; each of the constructs provided a basis for answering the research questions.

Nature of the Study

This study was a quantitative, correlational design of a cross-sectional nature using secondary data. A correlational design is commonly used to describe the pattern of relationships between variables for secondary data (Field, 2013). The research employed cross-sectional design because the secondary data was collected at a one point in time and did not require random assignment of individual cases to comparison groups (Field, 2013). Secondary data was obtained from the Health Information and Management Systems Society (HIMSS) Analytics, (2016) databases for nonfederal acute care hospitals, and the American Hospital Association (AHA) Annual Survey Database (AHA

Data Viewer, 2014; AHA Data Viewer, 2017).

The secondary data sources used for this study have been used by a number of researchers and are highly regarded for their integrity and reliability (Furukawa, Raghu, & Shao, 2010; Jones, Rudin, Perry, & Shekelle, 2014; McCullough, Casey, Moscovice, & Prasad, 2010; Miller & Tucker 2011; Appari, Carian, Johnson, & Anthony, 2012). This research design was chosen because it allowed the study to produce information about the relationships between EHR software application attributes, hospital characteristics, EHR implementation processes and their impact on the successful implementation of Stage 1 Meaningful Use. This may help policy makers, health systems, and practice leaders tailor policies and allocate resources effectively and to support providers in practice settings that may otherwise not able to demonstrate MU.

The correlational design was used to examine the relationship between two or more variables. The research problem, research question(s), and population group sought to explain the relationship between the independent and dependent variables (Field, 2013). To compensate for the limitations of cross-sectional evaluation design and correlational analyses, statistical analyses was used to calculate the relationship between the EHR software application attributes, hospital demographics and the successful implementation of Stage 1 Meaningful Use, and associated the variables to the hypothesis for this study. For the purpose of this study, the population was not split into a control group because the relationship between Electronic Health Records software application attributes (independent variable), hospital demographics (independent variable) and Meaningful Use objectives (dependent variable) could be studied.

The use of secondary data eliminated resource constraints in the data retrieval or design approach for this study. The nonexperimental use of secondary dataset also eliminated the time and resources required to recruit, participate, and collect data for this study. The data source supported the study with data sharing and required minimal resources (time) by the data provider. A data use agreement was signed to streamline the approval process. The quantitative, nonexperimental design was predicated on the research question, the type of variables, and the use of secondary data (Meadows, 2003).

The independent variables include hospital facility type, organizational control, ownership status, profit status, location/ region, and size. These variables were used to determine the relationship between the characteristics of hospitals and EHR software application attributes, and whether those relationships affect their attestation of MU. There were two dependent variables for this study. The first dependent variable was EHR software application attributes which consisted of Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE). The second dependent variable for this study was the implementation of Stage 1 Meaningful Use objectives. This variable comprised of Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information. This variable was used to determine the extent to which hospital demographics and the characteristics of the EHR software application could influence the attainment of MU objectives.

The target population for this study comprised of nonfederal acute care hospitals in 50 states and the District of Columbia (AHA Data Viewer, 2014; AHA Data Viewer, 2017; Health Information and Management Systems Services Analytics, 2016). The number of hospital organizations which were included in this study was based on a survey of non-federal acute-care hospitals in the USA. This study used secondary data sources so the target population was represented by the datasets available from those sources. The potential size of the study was a purposive convenience sample which represented all hospitals that reported and whose data was included in the data set. The sampling strategy for this study was a purposive convenience sampling method. The main characteristic of a purposive convenience sample is that participants are easy to access, available because of geographic location, and are not predicated on any predetermined variables (Cunningham, & McCrum-Gardner, 2007; Devane, Begley, & Clark, 2004). The power analysis results indicate that data from 174 hospitals should be included; however, all cases in the secondary data source will be used. The data was analyzed using correlation analysis and multiple linear regression analysis to address the statistical predictive relationship between hospital attributes and EHR software application attributes, and to address the statistical predictive relationship between EHR software application attributes and the successful implementation of Stage 1 Meaningful Use objectives.

Definitions

Following are the definitions of the terms and phrases which were used throughout this study:

Computerized Provider Order Entry (CPOE): A CPOE is an order entry application specifically designed to assist practitioners in creating and managing medical orders for patient services or medications. This application has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes (Centers for Medicare and Medicaid Services, 2016C). CPOE serves as a tool to increase standardization, quality, and efficiency in the delivery of care provided to patients in healthcare organizations (Kruse, & Goetz, 2015). Advantages accrued from implementing a CPOE system include decrease in adverse drug events (ADEs) and in medication errors in the form of incorrect dosages, incomplete orders, drug allergies, and abbreviation errors (Bates, Cohen, Leape, Overhage, Shabot, & Sheridan, 2001; Kohn, Corrigan, & Donaldson, 2000). CPOE may also reduce medication override dispense rates from automated dispensing cabinets (ADCs), improve the mean turnaround time (TAT) for first-dose medications, increase productivity, and decrease the amount of time from medication dispensing to medication administration (Kruse, & Goetz, 2015).

Meaningful use objectives: Meaningful Use (MU) involves employing EHR technology which is certified by the Centers for Medicare and Medicaid Services (CMS) to improve quality, safety, efficiency, and to reduce health disparities (Centers for Medicare and Medicaid Services, 2016B). It involves partnering with patients and their relatives to promote their health care, improving care management, improving public health and preserving the privacy and welfare of all participants (Centers for Medicare and Medicaid Services, 2016B). The Recovery Act specified three components of MU which involve consequential application of certified EHR (e.g., e-prescribing), using certified EHR technology for electronic exchange of health information to improve the quality of health care and to produce clinical and other quality measures (CQM) (Centers for Medicare and Medicaid Services, 2016B).

"Meaningful use" can be defined by the three requirements articulated in the Final Rule which encapsulates and implements the statutory requirements of the HITECH Act (Centers for Medicare and Medicaid Services, 2016B). The requirements comprise substantive use of certified EHR technology (e.g., e-prescribing); use of certified EHR technology in a manner that provides for electronic exchange of health information to advance the quality of care, and use of certified EHR technology to produce clinical quality measures (CQM) and other measures determined by the HHS Secretary. The Centers for Medicare and Medicaid Services intends to implement meaningful use requirements in three stages. Stage 1 focuses on capturing and sharing electronic health information at fundamental levels and establishing capabilities for data exchange and reporting data to various agencies. Stage 2 will build on the requirements of Stage 1 with more rigorous expectations for health information exchange and for additional EHR functionalities. Stage 3 will concentrate on promoting and making improvements that lead to improved health outcomes both at the individual and at the population levels, including greater use of decision support tools and patient access to self-management tools (Regulations and Guidance (DeSalvo, Dinkler, & Stevens, 2015).

Electronic Health Records: An EHR is a digitized patient health report which can be accessed by patients and health care professionals (Mishra, Anderson, Angst, & Agarwal, 2012; House & Mishra, 2015; McGinn, Grenier, Duplantie, Shaw, Sicotte, Mathieu, & Gagnon, 2011). EHR systems capture current and historical health data in electronic format and can potentially enhance communication between physicians and patients by generating health data more promptly (Nguyen, Bellucci, & Nguyen, 2014; International Organization for Standardization, 2005; Katehakis, & Tsiknakis, 2006). The concept of EHRs is a comprehensive documentation of a patient's healthcare information; including workflow surrounding the patient's care (House & Mishra, 2015). Benefits of EHRs include unifying fragmented data, reducing errors, improving decision making, and cutting costs (Mishra, et al., 2012; Kumar & Bauer, 2011). In order to be available to multiple stakeholders, EHRs need to accessible from different systems by authorized health providers or be interoperable. An interoperable electronic health record (EHR) is defined as a secure and private electronic lifetime record of an individual's key health history and care within the health system (McGinn, Grenier, Duplantie, Shaw, Sicotte, Mathieu, & Gagnon, 2011). This record is available electronically to authorized health providers and the individual anywhere, anytime in support of high quality care. This record is designed to facilitate the sharing of data across the continuum of care, across healthcare delivery organizations, across time and across geographical areas (McGinn et al., 2011). The EHR typically contains information such as existing health conditions, physician visits, hospitalizations, test results, and prescribed drugs.

Medication Errors: Medication errors are the most common type of medical errors reported in hospitals (Berdot, Gillaizeau, Caruba, Prognon, Durieux, & Sabatier, 2013). They are attributed to poorly designed systems and can be addressed by building more robust systems like CPOE, which prescribe medication orders electronically and improve clinical decision-making through advice, alerts and reminders (Institute of Medicine, 2006). Analyses of cases involving medication errors show that prescribing errors and administration errors are the most commonly reported medication errors in hospitals worldwide (Berdot et al., 2013; Lewis, Dornan, Taylor, Tully, Wass, & Ashcroft, 2009). Medication errors are common in the hospital setting and can lead to adverse drug events (Cousins, & Heath, 2008). An adverse event is defined as a harm to a patient or resident as a result of medical care or in a health care setting. It is an event that result in one of the four most serious categories of the National Coordinating Council for Medication Errors Reporting and Prevention (NCC MERP) Patient Harm Index, which comprise prolonged Skilled Nursing Facility (SNF) stay or hospitalizations (including emergency room visit), permanent harm, life-sustaining intervention, or death (Levinson, 2014).

Other types of medication errors include prescription errors, medication delivery errors and administration errors, which are the leading types of errors in hospitals (Hicks, Cousins, & Williams, 2004). Medication error rates are often used to compare drug distribution systems and to assess the effects of interventions (Barker, Pearson, Hepler, Smith, & Pappas, 1984; Dean, Allan, Barber, & Barker, 1995). They comprise errors with very serious consequences to those that have little or no impact on the patient. Errors that do not result in harm create additional work and can adversely affect patients' confidence in their care. As a result, equal importance is assigned to severity as well as the prevalence of errors (American Society of Health-System Pharmacists, 1993; Uzych, 1996).

Assumptions

The assumptions of the study included decisions regarding the use of secondary data. I used secondary data that was collected from nonfederal acute care hospitals in 50 states and the District of Columbia. The first assumption was the relationship between EHR software application attributes, hospital attributes and successful implementation of meaningful use objectives or all of the data that will be collected from the surveys. The secondary data included all self-submitted data from the hospitals in the 50 states and the District of Columbia. With the secondary data set there was an assumption that the information provided was truthful, represent actual outcomes within the organization and no information was falsified or omitted because of undesirable outcomes. During the data collection process, each organization authorized its Chief Executive Officer and primary quality leader to submit data on behalf of the organization; the assumption with the individual providing the information was that they had the authority to provide the data and had a good understanding of the hospital's operations. I assumed that every organization supplied the entire set of variables during the data collection procedures. I performed data cleaning according to sound research methods of coding missing data and removing incomplete submissions.

Scope and Delimitations

The scope of the study was defined by the secondary data collected from the hospital organizations. The study was designed for analysis of hospital level data and did not include patient level identifiers or patient health information (private health information). The secondary data was collected for the most recent reporting period. A delimitation of this study was my decision to focus on five of the fifteen core objectives selected as independent variables. These objectives were selected in order to manage the scope of the research, and they represent a reasonable cross-section of the core objectives. Finally, in this study, I did not investigate the methods used by the hospitals to conduct their operations; rather I focused on the EHR software application attributes implement and the hospital characteristics that influenced the successful implementation of Stage 1 Meaningful Use objectives.

Limitations

There were two anticipated limitations for the reliability and validity of the data collection tool used by the primary data source. The limitations included restricted reliability and validity testing of the HIMSS and AHA surveys prior to the use of such tools (George, Batterham, & Sullivan, 2003).

The leaders who completed the assessment tool could have had a bias responding to survey questions about their organization. Other limitations of the study included the unconscious bias for management decisions, and the impact of those decisions on the EHR software application attributes implemented and the successful implementation of Stage 1 MU objectives (Hassouneh, 2013). The studies was limited to the statistical relationship between EHR software application attributes implemented, hospital characteristics and the successful implementation of Stage 1 MU objectives. Recommendations of future researches will be provided following the analysis to demonstrate more direct or indirect prediction of the variables.

Significance

The purpose of this study was to measure the relationship between EHR software application attributes implemented and the extent to which they influence the successful implementation of Stage 1 MU for critical access hospitals. To the extent that MU impacts care delivery, demonstration of MU may have an impact on evaluating the care offered to Medicare and Medicaid patients (Shea et al., 2015). In light of the renewed efforts by the government on using EHRs for upgrading delivery of care and public health, it was crucial to analyze the circumstances that impacted how providers demonstrated MU by focusing on EHR software application attributes and hospital demographics to measure Stage 1 Meaningful Use (MU) objectives (Shea et al., 2015). The aim of this study was to produce information about the relationships between hospital attributes and EHR implementation which may assist policy makers, health systems, and practice leaders tailor policies and allocate resources effectively.

Several researchers have studied the extent to which hospital characteristics impact meaningful use for hospitals (Adler-Milstein, DesRoches, Kralovec, Foster, Worzala, Charles, Jha, 2015; Adler-Milstein, Everson, & Lee, 2014; Diana, Harle, Huerta, Ford, & Menachemi, 2014). The impact of this study on social change was to add the combination of implementation theory and NPT as alternate theoretical framework that can be used to evaluate the implementation EHR to meet MU objectives.

Additionally, I could not locate a single EHR related study that compared EHR software application attributes with the implementation of Stage 1 Meaningful Use objectives. Furthermore, I could not locate any study on meaningful use that employed that used the Normalization Process Theory (NPT) and Implementation Theory as the theoretical framework for their research questions; as a result, this study will fill a knowledge gap in the discipline. The absence of such studies created a research gap which this study aimed to fill by investigating the dynamics between EHR software application attributes, hospital attributes in a quantitative research study based on Implementation Theory.

Summary

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, which was signed as part of the ARRA, has played a pivotal role in promoting the adoption of comprehensive electronic health records (EHRs) in the United States (DesRoches et al., 2012). The HITECH program incentivizes hospitals to demonstrate their adoption and "meaningful use" of certified EHR systems in order to increase the number of US hospitals that use comprehensive electronic systems by 2020 (DesRoches et al., 2012). The main objective of the HITECH Act is to promote meaningful use of certified EHR technology. It authorized the establishment of an incentive payment program for eligible professionals (e.g., physicians) and eligible hospitals that achieve "meaningful use" of qualified EHRs and interoperable Health Information Technology (Centers for Medicare and Medicaid Services, 2016B).

The purpose of this study was to evaluate how hospital characteristics and EHR software attributes influenced the MU implementation process for the demonstration of

Stage 1 MU objectives). This study measured the predictive relationships between Electronic Health Records (EHR) attributes and Meaningful Use (MU) objectives by employing the Normalization Process Theory (NPT) and Implementation Theory as the theoretical framework to address two research questions. The independent variables included hospital facility type, organizational control, ownership status, profit status, location/ region, and size. These variables were used to determine the relationship between the characteristics of hospitals and EHR software application attributes, and whether those relationships affected their attestation of MU. There were two dependent variables for this study. The first dependent variable was EHR software application attributes which consist of Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status. The second dependent variable for this study was the implementation of Stage 1 Meaningful Use. This variable comprised of Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information. This variable was used to determine the extent to which hospital demographics and the characteristics of the EHR software application influenced the attainment of MU objectives.

The theoretical framework for this study were the normalization process theory (NPT) and implementation theory (May, 2013A). NPT defines implementation as a social process of communal action and provides a consistent framework for identifying factors that stimulate and impede the standard integration of complex interventions into normal practice by offering researchers a basis for representing varied contexts, structures, social norms, group processes and conventions (Murray et al., 2010). Implementation Theory provides a structure for investigating implementation of complicated interventions and a way to measure and analyze progress and results. This framework originated from NPT and includes the implementation of work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009).

The research design that was used for this study was quantitative correlational design because this type of research design is commonly used to describe the pattern of the relation between variables for secondary data. It is also the most appropriate design for this study because it facilitated the collection of data that supported or refuted the hypothesis of this study (Field, 2013). The research design was cross-sectional because the secondary data was collected at a one point in time. The cross-sectional approach did not require random assignment of individual cases to comparison groups (Field, 2013). To compensate for the limitations of cross-sectional evaluation design and correlational analyses, statistical analyses was used to measure the relationship between the EHR software application attributes, hospital demographics and the successful implementation of Stage 1 Meaningful Use, and associate the variables to the hypothesis for this study. For the purpose of this study, the population was not split into a control group because the relationship between Electronic Health Records software application attributes (independent variable), hospital demographics (independent variable) and Meaningful

Use objectives (dependent variable) could be studied.

Secondary data was obtained from the Health Information and Management Systems Society (HIMSS) Analytics Databases of nonfederal acute care hospitals in the United (Health Information and Management Systems Services (HIMSS) Analytics, 2016), and the American Hospital Association (AHA) Annual Survey Database (AHA Data Viewer, 2014; AHA Data Viewer, 2017). The use of secondary data eliminated resource constraints in the data retrieval or design approach for this study. The nonexperimental use of secondary dataset also eliminated the time and resources required to recruit, participate, and collect data for this study. The data source was prepared to support the study with data sharing and required minimal resources (time) by the data provider. A data use agreement was signed to streamline the approval process. The quantitative, nonexperimental design was predicated on the research question, the type of variables, and the use of secondary data (Meadows, 2003).

Several researchers have studied the extent to which hospital characteristics impact meaningful use for hospitals (Adler-Milstein et al., 2015; Adler-Milstein et al., 2014; Diana et al., 2014). The impact of this study on social change was to add the combination of implementation theory and NPT as alternate theoretical framework that could be used to evaluate the implementation EHR to meet MU objectives. Additionally, I could not locate a single EHR related study that compared EHR software application attributes with the implementation of Stage 1 Meaningful Use objectives. Furthermore, I could not locate any study on meaningful use that employed that used the Normalization Process Theory (NPT) and Implementation Theory as the theoretical framework for their research questions; as a result, this study filled a knowledge gap in the discipline. The absence of such studies created a research gap which I intended to fill by investigating the relationships between EHR software application attributes and hospital attributes.

Chapter 2: Literature Review

Introduction

MU requires EHR technology which is certified by the CMS to improve quality, safety, and efficiency and reduce health disparities (CMS, 2016b). It also requires collaborating with patients and families in their health care, improving care coordination, refining population and public health, and safeguarding the privacy and security of all participants (CMS, 2016b). The demonstration of MU has a significant impact on care delivery to Medicare and Medicaid patients, and this is evidenced in the U.S. government's support of the use of EHRs for upgrading delivery of care and public health (Shea et al., 2015).

Researchers who have studied the adoption of EHRs have raised concerns, however, about the quality of the data contained in EHRs after implementation especially in the area of recording and tracking of drug allergy in the medical information of patients, inadequate reporting of harmful drug reactions, partial coding, and erroneous coding for cause of death which resulted in documentation errors in death certificates (Haghighi et al., 2013; Paul & Robinson, 2012). The importance of the demonstration of MU makes a compelling case for exploring how providers demonstrate MU which would entail focusing on the relationship between EHR software application attributes implemented, and hospital demographics to measure Stage 1 MU objectives (Shea et al., 2015). The aim of this study was to locate information about the effects of hospital attributes on EHR implementation, which could potentially facilitate decision making for policy makers, health system administrators to tailor policies, allocate resources, and assist providers in practice settings that may otherwise not be able to demonstrate MU. Information in this chapter includes the search strategy used to locate relevant literature for this study, a discussion of the theoretical propositions of the selected theory, and a comprehensive review of previous research and related literature.

Literature Search Strategy

I conducted a literature review using resources from Walden University Library. The literature review includes government documents and peer-reviewed journals. The databases and search engines used to obtain literature for this review included (a) ProQuest Nursing & Allied Health Source, (b) ProQuest Health & Medical Complete, (c) EBSCO, (d) CINAHL & MEDLINE, (e) SAGE Premier, (f) Academic Search Complete, (g) ProQuest Central, (h) Science Direct, and (i) Google Scholar. The articles reviewed were quantitative or qualitative study designs. Key search words used included electronic health record (EHR), electronic medical record (EMR), EHR implementation, Computerized Physician Order Entry (CPOE), EHR attributes, "Meaningful Use" OR "MU," EHR data quality, documentation errors, and critical access hospital (CAH).

The parameters of the search covered 2012-2016. I conducted separate searches and generated more than 170 references which formed the basis for answering the research question and assured appropriate research method and design. The final study includes 140 total references, of which 130 references (92%) are peer-reviewed articles published within the last 5 years.

Theoretical Framework

The theoretical framework for this study consisted of NPT (May, & Finch, 2009) and implementation theory (May, 2013a, 2013b).

Normalization Process Theory (NPT)

As a theory, NPT is a social process of communal action. It provides a consistent framework for identifying factors that stimulate and impede the standard integration of complex interventions into normal practice by offering researchers a basis for representing varied contexts, structures, social norms, group processes and conventions (Murray et al., 2010). NPT focuses on what work needs to be done, by whom, how it is done, and the benefits and costs of the work that is done (May, 2013a).

Implementations occur within socially organized, evolving linkages called social systems. Implementations are also are populated by agents who operate within social structures or contexts that provide social roles and norms (Bunge, 2004; May, 2013a). Agents or actors are individuals and organizations that work together in health care settings and include health professionals, hospital managers, and patients (Bunge, 2004; May, 2013a). Implementations involving technological, behavioral, and organizational processes are prominent in health care practice; however, the relationships between their components are unpredictable to evaluate (Campbell et al., 2007). Researchers have focused on the clinical and cost effectiveness of complex interventions in the case of trials and other outcomes studies while process evaluations explain the steps involved in arriving at results and the components that facilitate or impede those outcomes (Campbell et al., 2007). Consequently, process evaluations have become a key focus for health services researchers (May, 2006; May et al., 2007b; May, Mair, Dowrick, & Finch, 2007a).

Propositions & constructs. The three major components of NPT include implementing work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009). The first of the three propositions of NPT states that complex interventions involve exchanges within a particular situation over time, during which time individuals and groups implement practices in social contexts within which they become routinely embedded (May & Finch, 2009). The second proposition affirms that implementation processes is comprise of four constructs (coherence, cognitive participation, collective action, and reflexive monitoring), which are influenced by elements that enhance or hinder inserting a practice in its social contexts (May & Finch, 2009). The third proposition involves the requirement for an uninterrupted action by individuals or groups in a complex intervention (May & Finch, 2009). Based on these propositions, it can be argued that NPT offers important perspectives into how new or modified work processes can be routinized in their respective social systems.

Coherence or sense-making. The coherence or sense-making construct addresses how actors specify their involvement in a practice (May, 2013a; May et al., 2007a). It also involves how embedding is influenced by elements that foster or obstruct the concerns of actors about the essence of the actions that people perform to meet specific goals (May & Finch, 2009). For an intervention to be successfully routinized, there must be shared knowledge by the actors (May, 2013a; May et al., 2007a).

Cognitive participation. Cognitive participation involves actors who are members of an identifiable practice group. It also involves an explanation of how membership is obtained. Embedding or normalizing is predicated on the actors involved in a procedure and by elements that foster or obstruct the involvement of the actors (May, 2013a; May et al., 2007a).

Collective action. Collective action entails the performance of actors in a complex intervention. Embedding is influenced by elements that foster or obstruct the ability of actors authorizing it, by work that describes and operationalizes a procedure, and by the communal effort of participants in it (May, 2013A; May et al., 2007A).

Reflexive monitoring. Reflexive monitoring describes information processing of the outcomes of the intervention. Embedding relies on work that explains and organizes a regular routine (May, 2013A; May et al., 2007A).

NPT was developed by researchers who focused on understanding the implementation of advanced and complicated interventions in healthcare settings (McEvoy et al., 2014; May et al., 2007B). NPT does not address the relationships between individual attitudes and behaviors but focuses on the treatment of knowledge across professional groups, and aims to understand the implementation of new knowledge by healthcare professionals (Murray, Burns, May, Finch, O'Donnell, Wallace, & Mair, 2011; Gallacher, May, Montori & Mair, 2011). It is analogous to theories of actor networks and diffusion of innovation (Galusky, 2008; Rogers, 1995) because it addresses the authenticity of the intervention and the function of opinion leaders. It is also concerned with understanding trust and connections within social networks in the context of new ideas (Harris, Provan, Johnson & Leischow, 2012; Doumit, Wright, Graham, Smith & Grimshaw, 2011).

Context & agency. Contexts are the physical, organizational, institutional and legislative frameworks that support or hinder resources, people and procedures (May et al., 2007). They can also be described as the infrastructure within social norms, rules and roles are enforced. The potential construct and the capacity construct emphasize contextual elements. Agency explains the actions and decisions that individuals and groups make when constrained by conditions and contingencies in the course of an implementation (May, 2013A). Agency influences proactive engagement by the individual or group in their development, improvement and adaptation over time (Bandura, 2001). The capability construct and the contribution construct highlight agency (May, 2013A; May et al., 2007A). Context and agency embody the four constructs of the implementation theory and provide a more streamlined approach to explain the key components of a complex intervention.

Implementation Theory

Implementation theory provides a structure for investigating implementation of complicated interventions and a way to measure and analyze progress and results. This framework originated from NPT and includes the implementation of work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009). It also explains implanting and incorporation of new ideas into healthcare settings and draws attention of researchers to potential challenges during the implementation of services (May 2006); Morrison & Mair, 2012; Murray et al., 2010). A complex intervention refers to organizing new or modified work while embedding involves standardizing or normalizing work, and integration refers to the process of making practices part of their social contexts (May & Finch, 2009; May, Mair, Finch, MacFarlane, Dowrick, Treweek, Rapley, Ballini, Ong, Rogers, et al., 2009). A complex intervention impacts both the individual and shared knowledge and the extent to which participants hold each other accountable (May & Finch, 2009; May et al., 2009; May 2013A; May et al., 2007A).

Constructs of theory. Implementation theory provides four constructs that help experts to identify and describe the components of implementations and their results (May, 2013A). The four constructs of implementation theory are capacity, potential, capability, and contribution which are at the core of the theory and are integrated to provide thorough explanations for the processes by which complicated interventions are inserted into health procedures (May & Finch, 2009; May et al., 2009; May, May et al., 2007A).

Capacity. The capacity construct focuses on the social systems within which implementations occur (May, 2013A). It describes social networks as important precursors for implementations because they provide contexts for relationships and information flow during the implementation of a complex intervention. These contexts, or social structural resources, include social norms or rules, roles, material and cognitive resources that govern the work that is done (May, 2013A). The theoretical basis for the capacity construct is the Strategic Action Field Theory (Fligstein & McAdam, 2011), which postulates that strategic action fields (SAFs) are the basic elements of communal action in society. It is comprised of actors with knowledge of one another, relationships, power distributions and rules. Organizations, extended families, social movements, and governmental systems are themselves made up of SAFs. The basic premise of the capacity construct is that the level of cooperation and collaboration that takes place in the course of a complex intervention is affected by the social roles, norms that regulate their conduct, and the material and information resources that available within that social structure (May, 2013A). In the context of this study, the capacity construct describes the attributes of the hospital as a social system within which EHR implementations occur.

Potential. The potential construct focuses on an individual agent's willingness to conform to social norms, roles and rules within a social system and highlights the value that stakeholders assign to new ideas, their attitudes, shared values and commitment (May, 2013A; May et al., 2007A). The basic premise of the potential construct is that an individual or group is able to achieve their goal of implementing a complex intervention only if they are willing or prepared to do so. Their willingness to implement the complex intervention is also driven by their experience and capability to complete their task (May, 2013A; May et al., 2007A).

Organizational readiness for change is a vital precondition for the successful implementation of new ideas in healthcare setups (Armenakis, Harris, & Mossholder, 1993; Hardison, 1998). It can be determined at the individual, group, or organizational level and it emphasizes shared resolve. Organizational changes such as EHRs, quality improvement programs and patient safety systems in healthcare delivery all require collective effort by constituents (Weiner, 2009). Purposeful individual intentions and the shared commitment towards the completion of tasks is important. In the context of this study, the potential construct describes the decisions and actions of healthcare practitioners and the hospital as an organizational unit during complex interventions such as EHR implementations.

Capability. The capability construct is drawn from the theory of normalization process and postulates that the capability of agents determines the extent to which new ideas or processes can be implemented to produce new opportunities (May, 2013a; Murray et al., 2010). The capability construct focuses on what is being implemented and describes the object of an implementation as a complex intervention (May, 2013a; Murray et al., 2010). When agents perform complex interventions, they employ multiple relations, interactions, techniques and technologies or organizational systems (May, 2013a; Murray et al., 2010).

The attributes of the components of a complex intervention – physical or virtual character, type of use, agent, and level of complexity – impact how they are used. The extent to which the qualities of a complex intervention can be incorporated into existing procedures is a crucial element of an implementation process (May, 2013A; Murray et al., 2010). Workability involves the interactions between users and the elements of a complex intervention; integration involves interactions between the circumstances of use and the elements of a complex intervention (May, 2013A; Murray et al., 2010). In the context of this study the capability construct describes the extent to which EHR implementation can be implemented in a hospital to produce new opportunities in the form of higher operational efficiencies, lower costs and improved patient safety (May, 2013A; Murray et al., 2010).

Contribution. Contribution addresses ongoing support from stakeholders as a key success factor in the implementation of new ideas (May, 2013A; Murray et al., 2010). Agents are part of social systems that are formed when social roles and norms are established through organized and evolving relations which promote information flows within the resulting social structures (May, 2013A; Murray et al., 2010). The social structures enable the formation and expression of individual intentions and collective commitments which lead to the completion of complex interventions (May, 2013A; Murray et al., 2010). In the context of this study the contribution construct provides a framework for locating agentic intentions during MU interventions.

Integration of capacity, potential, capability, & contribution. The combination of the capacity, potential, capability and contribution constructs illustrate the dynamics of a complex intervention and the alignment between the various components. The capacity construct provides the framework for transmission of information and interactions between individuals and groups, which are regulated by social norms or rules, roles, as well as physical and intellectual resources (May, 2013A). The potential construct provides the actors whose willingness and ability to operate within the established social norms, roles and rules of the framework are evidenced by their attitudes, shared values and commitment to the complex intervention (May, 2013A; May et al., 2007A). The capability construct determines the extent to which new ideas or processes can be successfully implemented by the actors in a social network to produce the desired outcome of an implementation (May, 2013; Murray et al., 2010). The contribution construct addresses the sustainability of the complex intervention which is determined by continued support from all constituents of a complex intervention (May, 2013A; Murray et al., 2010). The interactions between the constructs do not always occur in the same order because they integrative. Each of the above components is important and must be functional within the right context to assure the success of a complex intervention.

NPT and implementation theory were chosen for this study because they offered a way to identify and explain the dynamics between agentic expressions and different contexts within a complex intervention and provided a robust theoretical framework for addressing both individual and organizational level factors (Murray et al., 2010). The constructs of these theories were also germane to the key components of this study and, provided a firm basis for answering the research questions; each of the constructs provided a basis for answering the research questions.

Literature Review Related to Key Variables and/or Concepts

The process of reviewing literature entailed a theoretical and scholarly basis for the study by providing analysis and synthesis of peer reviewed articles and academic research relating to the research question. The review process covered the following areas: (a) current literature on EHR attributes, or software features and characteristics, and their influence on the implementation and adoption of EHRs; (b) implementation and adoption of EHRs; (c) demonstration of MU and (d) benefits and challenges of EHRs related to patient safety, quality, and cost of care.

System Attributes of Electronic Health Records

Safety, quality, and efficiency are the overarching goals of health care managers and they can be accomplished by leveraging information technology (IT) (Swindells, &

de Lusignan, 2012). IT is widely used to support and measure quality of clinical care, clinical consultation and primary care in the form of electronic health records (Swindells, & de Lusignan, 2012). IT saves time in issuing medication and improves legibility of prescriptions and records. Drug interactions are flagged in most operational systems, which have enormous potential to prevent errors (Vaziri, Connor, Shepherd, Jones, Chan, & de Lusignan, 2009).

An EHR stores patients' health information in a computer system. Electronic health records permit electronic documentation of current and historical health, tests, referrals, and medical treatments and enables practitioners to order tests and medications electronically. EHR systems have the potential to improve communication between physicians and patients by making data more readily available (Nguyen, Bellucci, & Nguyen, 2014; International Organization for Standardization, 2005; & Katehakis, & Tsiknakis, 2006). A computerized health system offers enormous opportunities for clinical decision support (Usenko, 2012). A significant challenge with computerization is the difficulty with incorporating new functionality into the clinical workflow and establishing an industry standard for such functionalities. This issue causes many versions of the same coding system across primary care systems, negatively impacts clinical coding and leads to issues like different calculation of cardiac risk when the same risk profile is inserted into different brands (Dostăl, Pavelka, Zvárová, Hanzlíček, & Olejárová, 2006).

There are several types of departmental information systems including the Computerized Physician Order Entry System (CPOE) which is one of the widely used

EHR systems. Computerized physician order entry (CPOE) systems allow clinicians to enter medication and other orders into a central electronic system which are then conveyed to other departments. The first CPOE system was implemented in the early 1970s for cost saving purposes but yielded other unexpected benefits in the form of legible display of dosage options, and alerts if physicians deviated from approved standards (Hodge, 1990). The CPOE system is regarded as a key technology for improving patient safety (Bates, Teich, Lee, Seger, Kuperman, Ma'Luf, & Leape, 1999; Leape, 1994). Benefits of the CPOE include elimination of ambiguous handwriting, direct connections to pharmacies, avoiding errors associated with similar drug names, and integrating patient information into medical records. CPOE systems can also be linked to decision-support systems, which offer reminders about dosages, drug interactions, and drug allergies.

Researchers who have studied CPOE adoption have highlighted key factors to successful implementation which include linkages to other health IT, motivated stakeholders, and influence of medical professionals (Lehmann, & Kim, 2006; Yui, Jim, Chen, Hsu, Liu, & Lee 2012). The success of CPOE adoption in hospitals depends on the degree to which it is linked to other systems, such as pharmacy, decision-support systems, electronic medical records (EMRs), and electronic medication administration record (e-MAR) systems (Jones et al., 2014). Motivated stakeholders include cost savings, patient safety and the role of regional or national heal IT policies (Ash, & Bates, 2005).

The structure of EHR systems is rarely explained by researchers and the lack of explanation provides limited reference point for standardization (Swindells, & de Lusignan, 2012). The lack of standards for EHR systems and attributes is a global healthcare issue but the process of standardizing health information systems for EHRs also will require standardization of their content and structure (European Commission, 2004). This lack of standardization allows EHR vendors to offer very different EHR systems that impacts what is recorded and affects overall healthcare delivery (Keyhani, Hebert, Ross, Federman, Zhu, & Siu, 2008). Each health care profession contributes separately to their respective departmental EHRs such as intensive care records, emergency department records or ambulatory records EHR. This separation of the record into sections according to profession creates problems with duplicate documentation at the summary level, is time consuming and may be unsafe because responsibility for the documentation is unclear between health professionals (Jensdóttir, Jónsson, Noro, Jonsén, Ljunggren, Finne-Soveri, & Björnsson, 2008; Törnqvist, Törnvall, & Jansson, 2016).

There are three categories of EHR structure and content including time-oriented, problem-oriented, and source-oriented and an EHR can have one or all of these components (Marek, Kneedler, Zielstorff, Delaney, Marr, Averill, & Millholland, 1996; Tange, Hasman, de Vries Robbé, & Schouten, 1997). In the time-oriented electronic medical record, the data are presented in chronological order. In the problem-oriented medical record (POMR), notes are taken for each problem assigned to the patient, and each problem is described according to the subjective information, objective information, assessments and plan (SOAP). In the source-oriented record, the content of the record is arranged according to the method (for example, notes of visits, X-ray reports and blood tests) by which the information was obtained. Within each section, the data are reported in chronological order (Tange et al., 1997). The American Nurses Association (ANA) has also developed a framework for nursing documentation which also corresponds with the SOAP structure for medical documentation (Marek et al., 1997).

Demonstration of Meaningful Use (MU)

Meaningful Use (MU) involves employing EHR technology which is certified by the Centers for Medicare and Medicaid Services (CMS) to improve quality, safety, efficiency, and to reduce health disparities (Centers for Medicare and Medicaid Services, 2016B). It involves partnering with patients and families in their health care, improving care coordination, improving population and public health and preserving the privacy and security of all participants (Centers for Medicare and Medicaid Services, 2016B). The writers of the Recovery Act specified three components of MU which involves consequential application of certified EHR (e.g., e-prescribing), using certified EHR technology for electronic exchange of health information to improve the quality of health care and to submit clinical quality measures and other measures (CQM) (Centers for Medicare and Medicaid Services, 2016B).

To successfully achieve Stage 1 Meaningful Use, hospitals must complete 14 core objectives, five objectives out of 10 from the menu set and 15 clinical quality measures. The 14 core objectives have been listed in Table 1, and five of the core objectives, which were selected as independent variables for this study, have been asterisked in the table.

Table 1

Meaningful Use: Stage 1Core Objectives

Health outcomes policy priority	Stage 1 objective	Stage 1 measure
Engage patients and families in their healthcare	Use CPOE for medication orders directly entered by any licensed healthcare professional who can enter orders into the medical record per state, local, and professional guidelines[a]	More than 30% of unique patients with at least one medication in their medication list admitted to the eligible hospital must have at least one medication entered using CPOE
	Implement drug-drug and drug-allergy interaction checks[a]	This functionality must be enabled for the entire EHR reporting period
	Record demographics: preferred language, gender, race, ethnicity, date of birth, and date and preliminary cause of death in the event of mortality in the eligible hospital or CAH	More than 50% of all unique patients seen by the EP or admitted to the eligible hospital or CAH have demographics as recorded structured data
	Maintain up-to-date problem list of current and active diagnoses	More than 80% of all unique patients seen by the EP or admitted to the eligible hospital or CAH have at least one entry or an indication that no problems are known for the patient recorded as structured data
	Maintain active medication list	More than 80% of all unique patents seen by the EP or admitted to the eligible hospital or CAH have at least one entry (or an indication that the patient is not currently prescribed any medication) recorded as structured data

(table continues)

Maintain active medication allergy list[a]	More than 80% of all unique patents seen by the EP or admitted to the eligible hospital or CAH have at least one entry (or an indication that the patient has no known medication allergies) recorded as structured data
Record and chart vital signs: height, weight, blood pressure, calculate and display BMI, plot and display growth charts for children 2-20 years, including BMI[a]	For more than 50% of all unique patients age 2 and over seen by the EP or admitted to the eligible hospital or CAH, height, weight, and blood pressure are recorded as structured data
Record smoking status for patients 13 years old or older	More than 50% of all unique patients 13 years or older seen by the EP or admitted to the eligible hospital or CAH have smoking status recorded as structured data
Implement one clinical decision support rule and the ability to track compliance with the rule	Implement one clinical decision support rule
Report clinical quality measures to CMS or the States	For 2011, provide aggregate numerator, denominator, and exclusions through attestation; For 2012, electronically submit clinical quality measures

(table continues)

Health Outcomes Policy Priority	Stage 1 Objective	Stage 1 Measure
Engage patients and families in their healthcare	Provide patients with an electronic copy of their health information (including diagnostic test results, problem list, medication lists, medication allergies, discharge summary, procedures), upon request	More than 50% of all unique patients of the EP, eligible hospital or CAH who request an electronic copy of their health information are provided it within 3 business days
	Provide patients with an electronic copy of their discharge instructions at time of discharge, upon request	More than 50% of all patients who are discharged from an eligible hospital or CAH who request an electronic copy of their discharge instructions are provided it
Improve care coordination	Capability to exchange key clinical information (ex: problem list, medication list, medication allergies, diagnostic test results), among providers of care and patient authorized entities electronically[a]	Performed at least one test of the certified EHR technology's capacity to electronically exchange key clinical information
Ensure adequate privacy and security protections for personal health information	Protect electronic health information created or maintained by certified EHR technology through the implementation of appropriate technical capabilities	Conduct or review a security risk analysis per 45 CFR 164.308(a)(1) and implement updates as necessary and correct identified security deficiencies as part of the EP's, eligible hospital's or CAH's risk management process

Note. Centers for Medicare and Medicaid Services. (2016A). Medicare & Medicaid EHR Incentive Program Meaningful Use Stage 1 Requirements Overview 2010: Meaningful Use: Core Objectives.
[a]Core objectives selected as independent variables for this study.

It entails partnering with patients and families in their health care, improving care coordination, improving population and public health and preserving the privacy and security of all participants (Centers for Medicare and Medicaid Services, 2016B). The writers of the Recovery Act specified three components of MU which involves consequential application of certified EHR (e.g., e-prescribing), using certified EHR technology for electronic exchange of health information to improve the quality of health care and to submit clinical quality measures and other measures (CQM) (Centers for Medicare and Medicaid Services, 2016B).

MU Stage 1 set the foundation for the EHR Incentive Programs by establishing requirements for the electronic capture of clinical data, including providing patients with electronic copies of health information (Centers for Medicare and Medicaid Services, 2016B). Hospitals demonstrate Stage 1 Meaningful Use by meeting 14 core objectives, five out of ten menu set objectives and 15 clinical quality measures (CQMs). Each of the objectives is associated with a health outcomes policy priority. These objectives and measures are designed to improve quality, safety, efficiency and reduce health disparities (Centers for Medicare and Medicaid Services, 2016B). Each of the objectives has a specific measure which determines whether that objective was met or not (Centers for Medicare and Medicaid Services, 2016B). With exception of the menu set objectives which requires only five out of the ten objectives to be met, 14 core objectives and 15 clinical quality measures must be completed (Centers for Medicare and Medicaid Services, 2016B). Other requirements of Stage 1 MU include reporting attestation in the form of yes/no or numerator/denominator with 80% of the patient records in the certified EHR technology.

The five core objectives that were selected for inclusion in this study include: using computerized provider order entry (CPOE) for medication orders directly entered by any licensed health professional who can enter orders into the medical record per state, local, and professional guidelines; implement drug-drug and drug-allergy interaction checks, maintain active medication allergy list; and record and chart vital signs; height, weight, blood pressure, calculate and display BMI, plot and display growth charts for children 2- 20 years, including BMI. To measure CPOE, more than 30% of unique patients with at least one medication in their list admitted to the eligible hospital must have at least one medication entered using CPOE. To measure the implementation of drug-drug and drug allergy interaction checks, the eligible hospital must enable this functionality for the entire EHR reporting period. To measure the maintenance of active medication allergy list, more than 80% of all unique patients seen by the eligible hospital must show at least one entry that the patient has no known medication allergies recorded. To measure the recording and charting of vital signs, the eligible hospital must demonstrate that for more than 50% of all unique patients age 2 and over who were admitted, height, weight and blood pressure were recorded as structured data. To measure the capability to exchange key clinical information among providers of care and patient authorized entities electronically, at least one test of the certified EHR technology's capacity to electronically exchange key clinical information must be performed (Centers for Medicare and Medicaid Services, 2016B).

DesRoches, Audet, Painter, and Donelan (2013) studied the proportion of physicians who are able to use electronic health records (EHRs) to manage patient populations and reported that measures of EHR adoption typically have focused on functionalities of systems and the ability of physicians to access and store information at the point of care. The most commonly adopted functionalities were viewing laboratory results, ordering prescriptions electronically, viewing radiology or imaging results, and recording clinical notes. The functionalities that were least likely to be adopted were exchanging patient clinical summaries and laboratory and diagnostic test results with outside entities, generating quality metrics, and providing patients with after-visit summaries and copies of their health information (DesRoches, Audet, Painter, & Donelan, 2013).

Quality of Health Care

The health care system in the United States has been facing significant challenges with high costs, poor quality, and unsteady performance (Smith, Saunders, Stuckhardt & McGinnis, 2013). Health information technology is seen as a key component to reducing costs and improving quality, efficiency and timeliness of healthcare delivery (Plsek, 2001as cited by Harle & Menachemi, 2012). The American Recovery and Reinvestment Act of 2009 (ARRA) (Pub.L. 111–5) was enacted to establish incentive payments to eligible professionals (EPs), eligible hospitals, critical access hospitals (CAHs), and Medicare Advantage Organizations, and to promote the adoption and meaningful use of interoperable health information technology (HIT) and qualified electronic health records (EHRs) (Centers for Medicare and Medicaid Services, 2016B).

The 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, which was signed as part of the ARRA, has been instrumental in driving adoption of comprehensive electronic health records (EHRs) across the United States (DesRoches et al., 2012). The HITECH program incentivizes hospitals to demonstrate their adoption and "meaningful use" of certified EHR systems to ensure that most US hospitals use comprehensive electronic systems by 2020 (DesRoches et al., 2012). The meaningful use criteria established by the HITECH Act specified the guidelines to incentivize qualified health care providers, facilities, and CAHs to employ EHRs in a meaningful way (Kennedy, 2013). The Centers for Medicare and Medicaid Services (CMS) allowed hospitals to begin attestation to successful achievement of the Stage 1 Meaningful Use (MU) requirements in 2011; by September 2016, $27.3 billion had been paid over 599,000 eligible professionals, eligible hospitals, and critical access hospitals who were registered with the Medicare and Medicaid EHR Incentive Programs (Centers for Medicare and Medicaid Services, 2016). DesRoches et al. (2013) concluded that the meaningful use incentive program has been successful at increasing the number of hospitals pursuing comprehensive EHR adoption.

Medication Errors

Medical errors, in particular medication errors, continue to be a troublesome factor in the delivery of safe and effective patient care. The majority of medication errors are associated with breakdowns in poorly defined systems, developing technologies and evolving workflows seem to be a logical approach to provide added safeguards against medication errors. The medication process in hospitals involves drug procurement, prescribing, dispensing, administering, and monitoring (Cronenwett, Bootman, Wolcott, & Aspden, 2007). Errors may occur are at every step of the medication process even though the majority of them occur during the prescribing and administering stages Berdot et al., 2013). On average, a hospital patient is subjected to more than one medication error each day (McDowell, Ferner, & Ferner, 2009; Cronenwett et al., 2007).

Analyses of cases involving medication errors show that prescribing errors and administration errors are the most commonly reported medication errors in hospitals worldwide (Berdot et al., 2013; Lewis, Dornan, Taylor, Tully, Wass, & Ashcroft, 2009). Medication errors are the most common type of medical errors reported in hospitals (Berdot et al., 2013). They are attributed to poorly designed systems and can be addressed by building more robust systems like CPOE, which prescribe medication orders electronically and improve clinical decision-making through advice, alerts and reminders (Institute of Medicine, 2006). Clinical decision-making is enhanced by using a software which matches patient data to a computerized clinical knowledge base to provide patient-specific assessments (Kuperman, Bobb, Payne, Avery, Gandhi, Burns, & Bates, 2007).

Some of the risk factors associated with administration errors involve nurses' interruption and drugs administered intravenously (Berdot, Sabatier, Gillaizeau, Caruba, Prognon, & Durieux, 2012; Westbrook, Woods, Rob, Dunsmuir, & Day, 2010). These risk factors can be mitigated through the use of technology in the form of a bedside bar-coded drug administration system, and implementation of CPOE (The Institute for Safe Medication Practices, 2002). A study by (van Doormaal, van den Bemt, Zaal, Egberts, Lenderink, Kosterink, & Mol, 2009) on the effect on medication errors after implementing CPOE with basic decision support based on the G-Standard showed a significant reduction in medication errors. Even though the researchers did not show an effect on actual patient harm they indicated that more advanced clinical decision support is needed. There are mixed results on medication errors after the implementation of CPOE. Han, Carcillo, Venkataraman, Clark, Watson, Nguyen, et al., (2005) reported unexpected increase in mortality; however, Ammenwerth, Schnell-Inderst, Machan, and Siebert (2008) reported a significant decrease in the risk of medication errors after the implementation of CPOE.

Mistakes may be inevitable and one of the best way to prevent future errors from occurring is to identify the failures that produced the errors and correct them (Stefanacci, & Riddle, 2016). Preventable medical errors account for more than 400,000 deaths each year, and are the third cause of death in the United States, behind heart disease and cancer (John, 2013). Medical errors cause approximately 10,000 complications or injuries every day resulting in costs to the country of more than $1 trillion each year (John, 2013). In order to improve error detection, reporting, improve medication safety and minimize future errors, there needs to be an ongoing process of focused and open learning from medication errors (The Institute for Safe Medication Practices, 2002). Staff awareness about conditions that could jeopardize patient safety must be enhanced to make more likely for staff to notice and report hazardous conditions (The Institute for Safe Medication Practices, 2002). Proactive use of information about hazardous conditions to prevent errors and reduce legal liability for poor patient outcomes due to adverse drug events must be promoted (The Institute for Safe Medication Practices, 2002).

Barriers to Implementation and Adoption of EHRs

Electronic health records are healthcare applications that digitize patient records and clinical workflows. EHRs consist of a Clinical Data Repository (CDR) that stores patient data, a Clinical Decision Support System (CDSS) that assists providers with reference information and suggestions for care, a Computerized Provider Order Entry (CPOE) that enable providers to electronically place orders, and a Physician Documentation (PD) system that consolidates clinical notes across hospital departments (Hydari, Telang & Marella, 2015). Well-designed EHRs can improve patient safety by improving communications, making knowledge accessible, providing decision support, requiring key pieces of information for correct treatment, assisting with calculations, performing real-time checks, and assisting with monitoring (Bates & Gawande, 2003).

Implementation of EHRs can be influenced at the micro level, meso level and the macro levels. It is influenced at the micro level by interpersonal factors such as individuals' attitudes and beliefs; at the meso-level by the operational aspects such as readiness and resources; and at the macro level by socio-political forces (Greenhalgh, Stramer, Bratan, Byrne, Mohammad, & Russell, 2008 as cited by Hogan-Murphy, Tonna, Strath, & Cunningham, 2015). One of the key objectives for implementing EHRs is to improve the quality of care by reducing medical errors, provide effective means of communication, sharing information between healthcare providers, and collecting health information for educational and research purposes (Miller & Sim, 2004; Valdes, Kibbe, Tolleson, Kunik, & Petersen 2004 as cited by Ayatollahi, Mirani, & Haghani, 2014). The process of creating and using EHRs is complex because it involves technical and nontechnical issues which could become barriers that make achieving predetermined goals difficult (Morton & Wiedenbeck, 2009). There are a number of barriers in implementation and adoption of EHRs; they include individual, technical, organizational, and financial (Ajami, & Bagheri-Tadi, 2013; Sadoughi, Delgoshaei, Foozonkhah, Tofighi, & Khalesi, 2006).

Individual or human barriers, Individual or human barriers may include the lack of awareness of the importance and benefits of using EMRs, lack of knowledge of and experience with using EHRs, and negative impressions about EHRs (Khalifa, 2013; McGinn, Gagnon, Shaw, Sicotte, Mathieu, Leduc, & Légaré, 2012). Communication between users has a significant impact on user acceptance especially when this has a negative impact on workflow (Castillo, Martínez-García, & Pulido, 2010). Workflow can also be impacted when the skills needed to listen to patients, assess medical intervention simultaneously type notes are negatively impacted due to lack of familiarity or confidence with system use (Castillo et al., 2010). Resistance of clinical staff, especially physicians, due to failure to address their concerns is a major barrier to EHR implementation (Boonstra, Versluis, & Vos, 2014; McGinn, Gagnon, Shaw, Sicotte, Mathieu, Leduc, & Légaré, 2012). EHRs are a complex part of the field of e-health and they present a number of challenges in spite of their benefits (Khalifa, 2013; McGinn et al., 2012). The authors emphasized the importance of the need for providers and policy leaders to work together to address several challenges that tend to slow the rate of implementation and adoption of EHRs (Ajami, Ketabi, Saghaeian-Nejad & Heidari, 2011; Castillo et al., 2013; McGinn et al., 2012).

*Technical barriers***.** Technical barriers comprise lack of efficient hospital information systems and lack of national standards for data exchange, are more significant (McGinn et al., 2012; Miller & Sim, 2004; Sadoughi et al., 2006). Technical barriers also include lack of computer skills such as typing and familiarity with user interface, navigation between screens, menu selections and other system options can result in slower clinical decision and loss of productivity (Ross, 2009). Gartee (2007) also confirmed that hardware infrastructure, networks and information systems are among the most important factors influencing EHR adoption. Similarly, Sadoughi et al., (2006) and Thakkar, and Davis, (2006) found technical problems related to data exchange between different systems as the most significant barrier in EHR implementation and adoption. The above authors showed the importance of assessing the technical infrastructure, equipment and standards prior to the adoption of EHRs to prevent possible failures. Additionally, EHRs are applications that rely on efficient and effective systems to meet their technical, operational and organizational objectives (Sadoughi et al., 2006; Thakkar, & Davis, 2006).

*Organizational barriers***.** Organizational barriers may be caused by workflow redesign to complement EHR requirements, the lack of management experience to choose and implement an EHR application that will work best for the organization, and lack of expertise to evaluate the performance of EHRs (Khalifa, 2013). Workflow redesign can result in workflow disruption and work culture as the need to acquire new skills needed to interact with patients and colleagues while navigating a new system with new menus and screen (Castillo et al., 2010). Concerns about security and privacy for electronic patient data can translate into lack of confidence and reliability (Rao, DesRoches, Donelan, Campbell, Miralles, & Jha, 2011).

*Financial barriers***.** Financial barriers may be caused by high initial cost of EHRs implementation and adoption, lack of capital resources to invest in EHRs, high operational and maintenance costs, and the uncertainty about existing return on investment after implementing and adopting EHRs (Khalifa, 2013; McGinn et al., 2012). Adler-Milstein et al., (2015) found substantial progress in EHR adoption and meaningful use in U.S. hospitals. This change was attributed to the HITECH incentives for the meaningful-use program. Even though the HITECH law of 2009 was designed cover a significant portion of the investment related to demonstration of meaningful use, yet it may not suffice for all healthcare organizations McGinn et al., 2012).

Facilitators to Implementation and Adoption of EHRs

Successful implementation requires a high level of collaboration between different stakeholders and the contextual nature of implementation means that all the component of the process need to come together to facilitate the overall objective of any implementation (Spetz, Burgess, & Phibbs, 2012; Safdari, Ghazisaeidi, & Jebraeily, 2015). McGinn et al., (2011) studied the perceptions of healthcare professionals about the facilitators of EHR implementations and reported that increased patient safety, faster and easier access to patients' history, navigable and reliable, adequate staff training, and improved interdepartmental communication were among the factors that facilitated implementation of EHRs. Patient safety refers to freedom from accidental or preventable injuries produced by medical care (Institute of Medicine, 2001). It emphasizes an approach to care delivery that prevents errors, it enhanced lessons learned from past mistakes and a work environment that promotes safety among healthcare professionals, practices and patients. There is a direct correlation between minimizing avoidable errors and improving patient safety (Institute of Medicine, 2001; PSNet: Patient Safety Network, 2010). Faster and easier access to a patient's drug history is pivotal to making the right decisions for patients because it allows healthcare professionals to conduct comprehensive patient overview which makes it easier to modify patients' drug lists (Culler, Jose, Kohler, & Rask, 2011; Rahmner, Eiermann, Korkmaz, Gustafsson, Gruvén, Maxwell, & Vég, 2012). A reliable and user friendly system is one that is easy to navigate, has high data integrity and enhances user acceptance because it makes the work of healthcare professionals much easier (Spetz et al., 2014). Users are more likely to embrace an EHR system that they perceive the system as beneficial for their own work practice. IT support team that is able to respond quickly to system issues, training staff that can help users overcome system issues and answer questions can mitigate negative user sentiments. Additionally, a flexible implementation schedule that offers users enough time to adapt to new workflow processes and be comfortable with the new system all contribute to better user experience and acceptance (Georgiou, Ampt, Creswick, Westbrook, & Braithwaite, 2009).

Summary and Conclusions

The demonstration of Meaningful Use (MU) has a significant impact on care delivery to Medicare and Medicaid patients and this is evidenced in the United States government's support of the use of Electronic Health Records (EHRs) for upgrading delivery of care and public health The importance of the demonstration of MU requires a thorough understanding of the factors that influence how providers demonstrate MU by focusing on EHR software application attributes and hospital demographics to measure Stage 1 Meaningful Use (MU) objectives. The purpose of this study is to evaluate how hospital characteristics and EHR software attributes influence the MU implementation process for the demonstration of Stage 1 MU objectives. The outcome of the above investigations will help policy makers, health systems, and practice leaders tailor policies and allocate resources effectively and to support providers in practice settings that may otherwise not able to demonstrate MU. Meaningful Use (MU) was established under the American Recovery and Reinvestment Act of 2009 (ARRA) and it authorized the Centers for Medicare and Medicaid Services (CMS) to set standards for healthcare organizations to meet. The criteria comprise meaningful application of certified EHR (e.g., e-prescribing) and using certified EHR technology for electronic exchange of health information to improve the quality of health care and to satisfy clinical quality measures (CQM. In order to achieve Stage 1 Meaningful Use, hospitals must complete 14 core objectives, five objectives out of 10 from the menu set and 15 clinical quality measures designed to improve quality, safety, efficiency and reduce health disparities (Centers for Medicare and Medicaid Services, 2016B). The five objectives chosen for this study were drive by data availability and this could be a limitation for this study.

Implementation Theory was chosen for this study because it provides a framework for evaluating implementation of complex interventions and a way to measure and analyze progress and results. This framework originated from NPT and includes the implementation of work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts. NPT describes implementation as a social process of collective action and provides a consistent framework for identifying factors that promote and inhibit the routine incorporation of complex interventions into everyday practice Implementation Theory provides four constructs that help researchers and practitioners to identify and explain the components of implementation processes and their outcomes (May, 2013A; May, 2013B). The four constructs of Implementation Theory are capacity, potential, capability, and contribution; they are at the core of Implementation Theory and are integrated to provide thorough explanations for the processes by which complex interventions become routinely embedded in health care practice. The combination of the capacity, potential, capability and contribution constructs illustrate the dynamics of a complex intervention and the alignment between the various components. The capacity construct provides the framework for transmission of information and interactions between individuals and groups, which are regulated by social norms or rules, roles, as well as physical and intellectual. The potential construct provides the actors whose willingness and ability to operate within the established social norms, roles and rules of the framework are evidenced by their attitudes, shared values and commitment to the complex. The capability construct determines the extent to which new ideas or processes can be successfully implemented by the actors in a social network to produce the desired outcome of an implementation (May, 2013A; May, 2013B;

Murray et al., 2010). The contribution construct addresses the sustainability of the complex intervention which is determined by continued support from all constituents of a complex intervention (May, 2013A; May, 2013B; Murray et al., 2010). Contexts are the physical, organizational, institutional and legislative structures that enable and constrain resources, people and procedures (May et al., 2007A; May et al., 2007B). Agency explains the actions and decisions that individuals and groups make when constrained by conditions and contingencies in the course of an implementation (May, 2013A; May, 2013B). Context and agency embody the four constructs of the implementation theory and provide a more streamlined approach to explain the key components of a complex intervention.

Implementation Theory was chosen for this study because it offers a way to identify and explain the dynamics between agentic expressions and different contexts within a complex intervention and provides a robust theoretical framework for addressing both individual and organizational level factors (Murray et al., 2009). The constructs of the Implementation Theory are also germane to the key components of this study and, provide a firm basis for answering the research questions. The Implementation Theory was also selected for this study because each of the constructs of the theory provides a basis for answering the research questions. There are a number of barriers in implementation and adoption of EHRs; they include individual, technical, organizational, financial, and legal barriers (Sadoughi et al., 2006).

Chapter 3: Research Method

Introduction

The 2009 HITECH Act, which was signed as part of the ARRA, has been instrumental in driving adoption of comprehensive EHRs across the United States (DesRoches et al., 2012). The HITECH program incentivizes hospitals to demonstrate their adoption and "meaningful use" of certified EHR systems to ensure that most U.S. hospitals use comprehensive electronic systems by 2020 (DesRoches et al., 2012). The MU criteria established by the HITECH Act was the basis for the guidelines to incentivize qualified health care providers, facilities, and CAHs to employ EHRs in a meaningful way (Kennedy et al., 2013).

The CMS approved requests for attestation to successful achievement of the Stage 1 Meaningful Use (MU) requirements by hospitals in 2011 (CMS, 2016). By September 2016, $27.3 billion had been paid to more than 599,000 eligible professionals and hospitals and critical access hospitals who were registered with the Medicare and Medicaid EHR Incentive Programs (CMS, 2016). DesRoches et al. (2013) concluded that the MU incentive program has been successful at increasing the number of U.S. hospitals pursuing comprehensive EHR adoption.

MU involves employing EHR technology which is certified by the CMS to improve quality, safety, and efficiency and reduce health disparities (CMS, 2016b). It involves partnering with patients and families in their health care, improving care coordination, improving population and public health, and preserving the privacy and security of all participants (CMS, 2016b). The demonstration of MU has an impact on care delivery to Medicare and Medicaid patients, which is evidenced in the U.S. government's support of the use of EHRs for upgrading delivery of care and public health (Shea et al., 2015).

A number of researchers who have studied the adoption of EHRs have raised concerns about the quality of the data contained in EHRs after implementation. Such concerns involve mediocre recording and tracking of drug allergy in the medical information of patients, inadequate reporting of harmful drug reactions, partial coding, and erroneous coding for cause of death which resulted in documentation errors in death certificates (Callen, 2014; Haghighi et al., 2013; Harteloh, De Bruin, & Kardaun 2010; Paul & Robinson, 2012). The importance of the demonstration of MU underscores the need to investigate how providers demonstrate MU. This can be done by focusing on the relationship between EHR software application attributes implemented, and hospital demographics to measure Stage 1 MU objectives (Shea et al., 2015). This study required a specific research design and rationale for sound analysis of secondary data. These following sections include information on the variables, research design and rationale, and methodology that were used. I also discuss validity threats including ethical concerns.

Research Design and Rationale

In this section, I described the independent and dependent variables and explained how the research design addressed the research questions for this study. I also described the time and resource constraints related to the design choice and indicated how the design choice enhanced knowledge sharing in the discipline.

Variables

The independent variables included hospital facility type, organizational control, ownership status, profit status, location/region, and size. These variables were used to determine the relationship between the characteristics of hospitals and EHR software application attributes, and whether those relationships affect their attestation of MU. There were two dependent variables for this study. The first dependent variable is EHR software application attributes, which consist of Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE). EHRs are digital repositories of patient data that are accessible to multiple stakeholders (Angst et al., 2010; Ginn et al., 2011).

The second dependent variable for this study was the implementation of Stage 1 MU. This variable comprised of Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information. This variable was used to determine the extent to which hospital demographics and the characteristics of the EHR software application can influence the attainment of MU objectives.

Research Design

The research design that was used for this study is a correlational quantitative design. I chose this type of research design because it is commonly used to describe the pattern of relation between variables for secondary data (see Field, 2013). It was also the most appropriate design for this study and allowed for the collection of data that will support or refute the hypothesis of this study (Field, 2013). The research design was cross-sectional because the secondary data was collected at a one point in time. The cross-sectional approach was not require random assignment of individual cases to comparison groups (see Field, 2013). Secondary data was obtained from the Health Information and Management Systems Society (HIMSS) Analytics Databases of nonfederal acute care hospitals in the United (HIMSS Foundation, n.d. A), and the AHA Annual Survey Database (AHA Data Viewer, 2014).

The secondary data sources used for this study have been used to conduct a number of studies and are highly regarded for their integrity and reliability (Appari et al. 2012; Furukawa et al., 2010; Jones et al., 2014; McCullough et al., 2010; Miller & Tucker 2011). I chose this research design because it allowed me to produce information about the effects of EHR software application attributes, hospital characteristics, and EHR implementation processes on the successful implementation of Stage 1 MU. This information may help policy makers, health systems administrators, and practice leaders tailor policies and allocate resources effectively and to support providers in practice settings that may otherwise not able to demonstrate MU.

A correlational design was used to examine the relationship between the variables. The research problem, research questions, and population group will form the basis for explaining the relationship between the independent and dependent variables (Field, 2013). I used statistical analyses to calculate the relationship between the EHR software application attributes, hospital demographics, and the successful implementation of Stage 1 MU, and explained the outcomes based on the hypothesis for this study. For the purpose of this study, the population was not split into a control group because the relationship between EHR software application attributes (independent variable), hospital demographics (independent variable), and Meaningful Use objectives (dependent variable) can be studied.

The use of secondary data was eliminate resource constraints in the data retrieval or design approach for this study. The nonexperimental use of secondary dataset was also eliminate the time and resources required to recruit, participate, and collect data for this study. The data source was prepared to support the study with data sharing and required minimal resources (time) by the data provider. A data use agreement was signed to streamline the approval process. The quantitative, nonexperimental design was predicated on the research question, the type of variables, and the use of secondary data (Meadows, 2003).

Methodology

The methodology section will cover the population, sampling, procedures, and data collection processes for the proposed study.

Population

The target population for this study will be comprised of nonfederal acute care hospitals in 50 states and the District of Columbia (AHA Data Viewer, 2014; HIMSS Foundation, (n.d. a). The number of hospital organizations which will be included in this study will be based on a survey of non-federal acute-care hospitals in the USA. This study will use secondary data sources so the target population will be represented by the datasets available from these sources. The potential size of the study will be a purposive convenience sample which will represent all hospitals that reported and whose data is included in the data set.

Sampling and Sample Procedures

Sampling strategy. The sampling strategy for this study will be a purposive convenience sampling method. The main characteristic of a purposive convenience sample is that participants are easy to access, available because of geographic location, and are not predicated on any predetermined variables (Cunningham, & McCrum-Gardner, 2007; Devane et al., 2004). This sampling strategy features sampling units that appear to be representative of the population but it is difficult to determine the probability of inclusion of a particular sampling unit in the sample because it is subjective; it also falls within reasonable cost and time parameters (Cunningham, & McCrum-Gardner, 2007; Devane et al., 2004). The key factor for the selection of hospitals will be their inclusion in the secondary data source. The power analysis results indicate that data from 174 hospitals should be included (see below) but all cases in the secondary data source will be used because I will have access to that database containing the data.

Power analysis. A power analysis was performed to determine the sample size adequate for this study. Cohen (1988) suggested that an effect size correlation of .50 was moderate and an effect size of .80 was large. An effect size correlation of .50 was used to measure the strength of the relationship between the independent variable, hospital characteristics, and the dependent variables, EHR software application attributes and Implementation of Stage 1 Meaningful Use (Meline, & Bailey, 2004). An alpha level of .05 provides a 95% probability that a Type I error did not occur (Cunningham, & McCrum-Gardner, 2007; Devane, Begley, & Clark, 2004). A statistical power of 0.95 was used because if a relationship exists between the independent variable and the dependent variable, there is an 95% chance the relationship will be detected (Cunningham, & McCrum-Gardner, 2007; Devane, Begley, & Clark, 2004). The statistical program G*Power was used to calculate the sample size (Faul, Erdfelder, Buchner, & Lang, 2009). The size of the sample used for this study was 1,500, which exceeds the required sample size of 174 calculated by G*Power. Results of the power analysis are displayed in Table 1.

Table 2

Sample Size Power Analysis

Effect size	Statistical power Level	Alpha level	Required sample Size
0.50	0.95	.05	174

Note. G*Power was used to calculate the power analysis (Faul, Erdfelder, Buchner, & Lang, 2009).

Procedures for Archival/Secondary Data

Recruitment procedures. All of the hospitals in the U.S. have been participating in the Health Information and Management Systems Society (HIMSS) Analytics Database and the AHA Annual Survey. The HIMSS Analytics Database was licensed from HIMSS Analytics and includes hospital characteristics and the operational status of clinical IT applications. HIMSS provides benchmarking reports to respondents as an incentive for participation (McCullough, 2008). The HIMSS Analytics data are used extensively by IT vendors and have been used widely in health services research (Yu, Menachemi, Berner, Allison, Weissman, & Houston, 2009; Ozcan, & Kazley, 2008). It is the most comprehensive database of hospital IT adoption decisions in the U.S. and has been available since the late 1980s (McCullough, 2008). Since 1946, the American Hospital Association has conducted its Annual Survey of hospitals to assemble a comprehensive and dependable database on hospitals. This database contains hospital-specific data items on more than 6,000 hospitals and in excess 450 health care systems, including more than 700 data fields which cover organizational structure, personnel, hospital facilities and services, and financial performance. The database is released annually in October (AHA Data, 2014)

Participation procedures. HIMSS has relationships with healthcare providers, policy makers and research organizations around the world and follows an annual process to update its database. HIMSS also collaborates sister associations to broaden its participant base. HIMSS sends out surveys to participating hospitals complete the surveys; HIMSS staff and volunteers also contact participants by phone to get clarifications of incomplete data. (HIMSS, n.d.). AHA sends surveys to over 5,000 US hospitals to be completed by heads of organizations. The surveys are followed by mailings and phone calls to non-respondents in order to assure higher response rates (AHA Data Viewer, 2014).

Reputability of sources. HIMSS administers a thorough review of its databases as part of its update process. The Dorenfest Institute provides detailed historical data, reports, and white papers about information technology use in hospitals and integrated healthcare delivery networks to universities, students under university license, U.S. governments (local, state and federal), and governments of other countries that will be using the data for research purposes (Health Information and Management Systems Services, Analytics, 2016). The HIMSS database has been extensively employed in health IT research (Appari et al. 2012; Furukawa et al., 2010; Jones et al. 2010; McCullough et al. 2010; Miller & Tucker 2011). Qualified applicants are also given access to other resources and tools, including access to the Dorenfest 3000+ Databases and the Dorenfest Integrated Healthcare Delivery System Databases from 1986 up to two years before the current year (Health Information and Management Systems Services Analytics, 2016). The second source of data will be the AHA Annual Survey Database (AHA Data Viewer, 2014; AHA Data Viewer, 2015) which is produced from the AHA Annual Survey of Hospitals and is a reliable resource for health services research. It contains close to 1,000 data points and provides meaningful perspectives. The AHA Annual Survey Information Technology hospital database contains updated healthcare technology data which is pertinent to the Health Information Technology for Economic and Clinical Health (HITECH) Act. The survey contains responses from over 3,500 hospitals on electronic clinical documentation, MU functionalities, CPOE, decision support and bar coding for medication tracking (AHA Data Viewer, 2014; AHA Data Viewer, 2015)

Permissions for access. Access to this secondary dataset have been granted by the Dorenfest Institute for Health Information Technology Research and Education database (HIMSS Foundation, n.d. A; HIMSS Foundation, n.d. B) and AHA (AHA Data Viewer, 2014; AHA Data Viewer, 2015) and are in Appendix A. To apply for access, I registered at the HIMSS Foundation site (HIMSS Foundation, n.d. B), and signed a Usage Agreement and Application for the Dorenfest Institute for H.I.T. Research and Education Database (HIMSS Foundation, n.d. A). I also signed a separate usage agreement with the AHA. HIMSS and AHA will send the data set via secure data transfer of encrypted email, from the data source. The data will be collected at the individual hospital level. Identifiable information for the hospital will include name, address, personnel names, or other tax/ identification numbers; however, the hospital's identification information will be de-identified.

Data collection. HIMSS follows an annual process to update its database. This involves initial data gathering conducted by phone followed by an IT inventory survey completed by hospital administrators (Health Information and Management Systems Services, n.d.). The AHA surveys are sent to the head of every US hospital to be completed. All non-respondents receive multiple mailings and follow-up phone calls to generate a high response rate. The most recent survey was sent to 6,377 hospitals between November 2014 and February 2015 (AHA Data Viewer, 2014). Hospitals are able to complete the survey online or by email. The AHA provides hospital data for accurate healthcare industry analysis. Each year, the AHA evaluates its database with the most pertinent indicators that reflect both historical and emerging trends (AHA Data Viewer, 2014). Preliminary updates to the AHA hospital database is provided monthly from April through September as updates to the AHA Annual Survey are received and validated. Data is finalized for the year in October (AHA Data Viewer, 2014).

Instrumentation and Operationalization of Constructs

The design of this study required use of a two-step approach to address the two research questions which were structured such that the second research question was dependent on the first. Consequently, there is one independent variable and two dependent variables for this study.

Hospital attributes. The independent variables for this study included hospital facility type, organizational control, ownership status, profit status, location/ region, and size. This variable will determine the relationship between EHR software application and the characteristics of hospitals and whether those relationships affect their attestation of MU. Diana et al., 2014) conducted a study that compared hospital bed size, profit status, location, teaching status, and compared with data obtained from the AHA Annual Survey and EHR Adoption Database to identify factors associated with hospitals that achieved meaningful use. The researchers reported that the hospitals receiving incentive payments were likely to be urban, larger, Joint Commission accredited teaching hospitals with a single health IT vendor that were full EHR adopters. The researchers also reported that hospitals located in the Mountain Pacific census division were less likely to have received MU payments, while those in the East North Central, New England, and South Atlantic census divisions were more likely to have received payments (Diana et al., 2014). In the Diana et al., (2014) study, researchers were able to identify hospitals that achieved MU on the basis of their attributes. Hospital attributes will be an important factor in answering the first research question for my study when its relationship with implemented EHR software application attributes is examined.

EHR software application attributes. The first dependent variable is EHR software application attributes which consist of Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE). EHRs are digital repositories of patient data accessible to multiple stakeholders (Angst et al., 2010; Ginn et al., 2011). The repositories capture patients' health, medical history, medical conditions, tests and treatments, medications, demographic information, and more (Kumar and Bauer, 2011). The above systems represent separate components of an EHR application, each with different attributes which are explained below in Table 2. Computerized provider order entry (CPOE) is used to explain EHR software application attribute as an independent variable for this study. Researchers examined the relationship between hospital CPOE and quality measures for clinical best practices in a 2011 study conducted by Swanson and Diana. The researchers selected ten process-related quality measures for three clinical conditions: acute myocardial infarction (AMI), congestive heart failure (CHF), and pneumonia as dependent variables; these variables had been used in previous studies by Jha et al. (2005) and Werner and Bradlow (2006) to analyze hospitals. They also selected CPOE, system membership, bed size, payer mix, ownership, case mix index, which are characteristics of hospitals, as independent variables. Swanson and Diana (2011) used the American Hospital Association (AHA) Annual Survey of Hospitals, Hospital Compare database, the Centers for Medicare and Medicaid Services (CMS) case mix index, and the HIMSS Analytics database. They also used a retrospective cross-sectional design and a quantitative research method. With the exception of the Centers for Medicare and Medicaid Services (CMS) case mix index, I plan to use the same data sources for this study. The Swanson & Diana (2011) study differs from my study in that it focused on a single EHR software application and its influence on the quality of the clinical decision making process. My study will focus on the relationships between hospital characteristics and EHR software application attributes of several EHR systems and their impact on the implementation of Stage 1 Meaningful Use.

Implementation of Stage 1 Meaningful Use. The second dependent variable for this study was implementation of Stage 1 Meaningful Use. This variable will be comprised of Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, exchange of key clinical information. For this study, implementation of Stage 1 MU will involve the steps that hospitals will follow to translate the required MU objectives into routine daily processes that can be sustained over time. It will also involve using a framework for evaluating and measuring the results of the implementation (May & Finch, 2009). This variable will be used to determine the extent to which hospital demographics and the characteristics of the EHR software application can influence the attainment of MU objectives. Shea et al., (2015) researched the relationship between practice characteristics and demonstration of Stage 1 Meaningful Use in a large integrated delivery system. The practice characteristics included practice specialty, size, mix of Medicare and Medicaid eligible providers and the Stage 1 MU objectives comprised of 14 core objectives and five menu objectives which are the same as the ones selected for my study. The researchers reported that practice characteristics were associated with providers' success in demonstrating MU objectives at the end of the first year of Stage 1, even when these practices are part of an integrated delivery system with a system-wide MU implementation strategy (Shea et al., 2015). The purpose of the Shea et al., (2015) study was to determine how practice characteristics influenced provider's ability to demonstrate MU and it is important to my study because it offers a quantitative approach which is relevant to my study.

Table 3

Dependent Variables

Variable	Subcategory / Term	Description
EHR Software Application Attributes	Cardiology information System	An application that specifically automates functions in the cardiology department. The application must provide some of the following: order processing, permanent patient history index maintenance, image and EKG tracing storage, transcribing and distributing results, clinical documentation, prep instruction cards maintenance, appointment scheduling, and management reporting.
	Health Information Management System – Electronic Forms	A software system that automatically generates forms and can be populated by importing data from another system and/or can export data that has been entered into another system.
	Ambulatory EMR System	The EMR that supports the ambulatory/clinic/physician office environments. Provides all of the functions of an EMR - clinical documentation/order entry/clinical data repository/provider order entry/physician clinical documentation/etc.

Table 3

Dependent Variables (cont)

Variable	Subcategory / Term	Description
	Utilization Review/Risk Management for Outcomes and Quality Management System	An application that provides a clinical data set utilized in monitoring overall performance, efficiency, cost, and quality of clinical care by analyzing, comparing and trending information of detailed clinical practice patterns and parameters. Example: To reduce infections post-operation, the hospital will gather data regarding broad or specific patients and can narrow down areas for improvement based on the data obtained.
	Information Sharing System	A program that lets one or more computer users create and access data in a database. On personal computers, Microsoft Access is a popular example of a single or small group user DBMS. Microsoft's SQL Server is an example of a DBMS that serves database requests from multiple users. This set of programs is used to define, administer, store, modify, process and extract information from a database.

Table 3

Dependent Variables (cont)

Variable	Subcategory / Term	Description
	**Computerized Provider Order Entry (CPOE)	An order entry application specifically designed to assist practitioners in creating and managing medical orders for patient services or medications. This application has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.
Implementation of Stage 1 Meaningful Use	**Computerized Provider Order Entry (CPOE)	An order entry application specifically designed to assist practitioners in creating and managing medical orders for patient services or medications. This application has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.

Table 3

Dependent Variables (cont)

Variable	Subcategory / Term	Description
	Drug-drug and drug-allergy interaction checks: CDSS-Electronic Drug Content Software	Provides clinical decision alerts and referential content to support sound treatment decisions in areas such as drug interaction checking (drug-drug and drug-food), drug allergy checking, therapeutic duplication checking, RxNorm Mappings, Drug Classifications, dose range checking (adult and pediatric) and provides patient specific alerts and referential content to support sound pharmacological treatment decisions.
	Active medication list system	An application used to evaluate and manage a patient's active medications as a patient moves between modalities of care using medication reconciliation software
	Record and chart changes in vital signs: Vital sign monitors (temp/NIBP/SPO2)	A device that monitors temperature, blood pressure measurements, and pulse (e.g. NIBP or Non-Invasive Blood Pressure, SPO2). These can be networked devices that write data to the EMR.

Table 3

Dependent Variables (cont)

Variable	Subcategory / Term	Description
	Exchange of key clinical information: Clinical Data Repository (CDR)	A centralized database that allows organizations to collect, store, access and report on clinical, administrative, and financial information collected from various applications within or across the healthcare organization that provides healthcare organizations an open environment for accessing/viewing, managing, and reporting enterprise information.

*Core objectives selected as independent variables for this study.
Note: Centers for Medicare and Medicaid Services. (2016A).
** Computerized Provider Order Entry (CPOE) is listed under both independent variables because it is used to answer the two research questions for this study.

Table 4

Independent Variables

Variable	Subcategory / Term	Description
Hospital Attributes	Facility Type - Hospital	A facility that services individuals with less than chronic diseases on an inpatient basis and provides a level of health care in which a patient is treated for a brief, but severe episode of illness, for conditions that are the result of disease or trauma and during recovery from surgery. Referred to as acute care facilities or hospitals.
	Organizational Control	This indicates the type of organization that is responsible for establishing policy for overall operation of the hospital. Options include Government, Non-Government, and Investor-Owned.
	Ownership Status - Leased Facility	An agreement with a facility or entity that has received rights of use and possession from another organization in accordance with the terms of a lease agreement and receives revenue for the facility or entity over a set number or years

Table 4

Independent Variables (cont)

Variable	Subcategory / Term	Description
	Ownership Status - Managed Facility	An agreement with a facility or entity in which managerial and purchasing control of IT is performed by another organization and they receive revenue from the facility or entity over a set period of years.
	Ownership Status - Owned Facility	A facility whose services are controlled and managed by the parent healthcare organization (HCO).
	Profit Status – For Profit	Established, maintained, or conducted for the purpose of making a profit (e.g. HCA, Tenet are for profit organizations)
	Profit Status – Not-For-Profit	Not conducted or maintained for the purpose of making a profit. A legal designation that confers tax exemption for the operation of the facility.
	Location / Region	Refers to the geographic area to which the system provides health care services.
	Size	Can be defined by staffed beds, discharges, admissions, surgical operations, patient days,

Data Analysis Plan

Analysis software**.** Data for this study will be accessed from the source organizations and placed in a secure external non-networked drive. The confidentiality of participants will be protected because they will not be identified in the release of information (data). SPSS (version 21) software will be used for all data analysis. The data will be analyzed through a series of multiple regression analyses between the multiple independent and dependent variables to establish their predictive relationships. These models of data are most suitable for describing the relationship between dependent variables and one or more independent variables (Laerd Statistics, 2013).

I will employ correlation analysis and multiple linear regression analyses to address the two research questions for this study. Correlation analysis and regression analyses use similar calculations but address different questions (Field, 2013; Tripepi, Jager, Dekker, & Zoccali, 2008). Correlation analysis focuses on the degree of association between two variables by evaluating the strength of the linear association between the variables. Multiple linear regression analysis highlights the linear dependence of a given independent variable on a given dependent variable (Field, 2013; Tripepi et al., 2008). For this study, correlation analysis and multiple linear regression analysis will be used to address the statistical predictive relationship between hospital attributes and EHR software application attributes for the first research question, and to address the statistical predictive relationship between EHR software application attributes and the successful implementation of Stage 1 Meaningful Use.

Nathans et al. (2012) reported that researchers employ multiple regression analysis to answer questions with two or more independent variables and one dependent variable. The regression analysis will determine if the regression coefficient is significantly different from zero (0). A p value of .05 or lower will also determine the extent to which the independent variables contribute significantly to the dependent variable (Allison, 1977). The hospital data will comprise acute-care hospitals that responded to the AHA and HIMSS annual surveys; as a result, small effect sizes measured by the standardized coefficients, will be considered untenable even if they are significant (Preacher, 2015). A large standardized coefficient will correspond to a large effect size as long as the independent variables are not correlated (Preacher, 2015). For this reason, I will test for multicollinearity among the independent variables prior to assessing the effect size.

The codebook which will be used to categorize and analyze the independent and dependent variables are listed in Table 4 and Table 5 below.

Table 5

Independent Variables Codebook

Variable	Subcategory / Term	Code	Description
Hospital Attributes	Facility Type - Hospital	1	Acute care facilities
		2	Hospitals
	Organizational Control	3	Government
		4	Non-Government
		5	Investor Owned
	Ownership Status	6	Leased Facility
		7	Managed Facility
		8	Owned Facility
	Profit Status	9	For-Profit
		10	Not-For-Profit
	Size	11	Licensed Beds
		12	Staffed Beds
		13	Rooms
		14	Discharges
		15	Admissions

		16	Surgical Operations
		17	Patient Days
	Location / Region - 1	18	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
	Location / Region - 2	19	New Jersey, New York, Pennsylvania
	Location / Region - 3	20	Delaware, Kentucky, Maryland, North Carolina, Virginia, West Virginia, District of Columbia

Table 5

Dependent Variables Codebook

Variable	Subcategory / Term	Code	Description
EHR Software Application Attributes	Cardiology Information System	1	Order Processing
		2	Permanent patient history index maintenance
		3	Image and EKG tracing storage
		4	Transcribing and distributing results
		5	Clinical documentation
		6	Prep instruction cards maintenance
		7	Appointment scheduling
		8	Management reporting
	Health Information Management System – Electronic Forms	9	Generates forms and can be populated by importing data from another system
		10	Export data that has been entered into another system
	Ambulatory EMR System	11	Clinical Documentation

	12	Order Entry
	13	Clinical Data Repository
	14	Provider Order Entry
	15	Physician Clinical Documentation
	16	Other
Utilization Review/Risk Management for Outcomes and Quality Management System	17	Provides clinical data set for monitoring overall performance, efficiency, cost, and quality of clinical care.
	18	Clinical data set for monitoring overall performance, efficiency, cost, and quality of clinical care not available.
	19	Provides clinical practice patterns and parameters.
	20	Clinical practice patterns and parameters not available.
Information Sharing System	21	Users can create and access data in a database.
	22	Users cannot create and access data in a database.
Computerized Provider Order Entry (CPOE)	23	Users can create and manage medical orders for patient services or medications.
	24	Users cannot create and manage medical orders for patient services or medications.
	25	System has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.

		26	System does not have special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.
Implementation of Stage 1 Meaningful Use	Computerized Provider Order Entry (CPOE)	1	Users can create and manage medical orders for patient services or medications.
		2	Users cannot create and manage medical orders for patient services or medications.
		3	System has special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.
		4	System does not have special electronic signature, workflow, and rules engine functions that reduce or eliminate medical errors associated with physician ordering processes.
	Drug-drug and drug-allergy Interaction checks: CDSS-Electronic Drug Content Software	5	CDSS Software supports treatment decisions in drug interaction checking (drug-drug and drug-food).
		6	CDSS Software does not support treatment decisions in drug

	interaction checking (drug-drug and drug-food).
7	CDSS Software supports treatment decisions in drug allergy checking (drug-drug and drug-food).
8	CDSS Software does not support treatment decisions in drug allergy checking (drug-drug and drug-food).
9	CDSS Software supports treatment decisions in therapeutic duplication checking.
10	CDSS Software does not support treatment decisions in therapeutic duplication checking.
11	CDSS Software supports treatment decisions in RxNorm Mappings.
12	CDSS - Electronic Drug Content Software does not RxNorm Mappings.
13	CDSS Software supports treatment decisions in Drug Classifications dose range checking (adult and pediatric).
14	CDSS Software does not support treatment decisions in Drug Classifications dose range checking (adult and pediatric).

		15	CDSS Software supports patient specific alerts and referential content for pharmacological treatment decisions.
	Active medication list system	16	Medication reconciliation software is used to manage patient's active medications as patient moves between modalities of care.
		17	Medication reconciliation software is not used to manage patient's active medications as patient moves between modalities of care.
	Record and chart changes in vital signs: Vital sign monitors (temp/NIBP/SPO2	18	Monitors temperature, blood pressure measurements, and pulse
		19	Other networked devices that write data to the EMR.
	Exchange of key clinical information: Clinical Data Repository (CDR)	20	CDR in use
		21	CDR not in use

Analysis software and cleaning**.** Analysis will be completed in the SPSS statistical software, with the latest updates and version for data entry and comparisons. Descriptive statistics, including means and standard deviations, will be completed prior to the data analysis for fit and normal distributions. Any data results that will be determined to be representing other demographic elements will be removed from the analysis. Multiple regressions will be used to analyze the findings of the following research questions and hypothesis:

RQ 1 – What is the predictive relationship between hospital attributes (facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status.

Null Hypothesis 1 ($H0_1$): There is no statistically predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status.

Alternative Hypothesis 1 (HA_1): There is a statistically significant predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status.

RQ 2 – What is the predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information

Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status and successful implementation of Stage 1 Meaningful Use (MU) objectives (Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information)

Null Hypothesis 2 ($H0_2$): There is no statistically significant predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - Electronic Forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status and successful implementation of Stage 1 Meaningful Use (MU) objectives (Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Alternative Hypothesis 2 (HA_2): There is a statistically significant predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and Computerized Provider Order Entry (CPOE) status and successful implementation of Stage 1 Meaningful Use (MU) objectives (Computerized Provider Order Entry (CPOE), drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Statistical testing. Multiple tests will be conducted to study the relationship between the EHR software attributes and hospital characteristics and their impact on the successful implementation of Stage 1 Meaningful Use. The statistical testing plan for each of the variables presented in this study will include both multiple linear regression tests and *t*-tests. There will be a series of correlation analysis and multiple linear regression analysis tests for analysis of hospital characteristics (independent variable), EHR software attributes (first dependent variable), and implementation of Stage 1 Meaningful Use (second dependent variable) to analyze their relationships to each of the dependent variables. These tests will be appropriate for the data because the dependent variables will be ordinal (number of occurrences), several independent variables will be used, and the test will indicate which will be the best predictors (California State University, Northridge. (n.d.). A series of *t*-tests will also be performed to analyze the difference between the hospital attributes, EHR software application attributes and successful implementation of Stage 1meaningful use based on the *t*-test. The *t*-tests, within the multiple linear regression analysis, will determine the degree of slope for the linear regression analysis and determine the strength of the relationship between the independent and dependent variables (Gabriel, Jones, Samy, & King, 2014).

Interpretation. The results of the multiple linear regression tests will be listed and displayed on regression charts for support for either the null or alternative hypotheses. The data will be provided in tabular format to compare the different range of relationships between the predictor and criterion variables.

Threats to Validity

A study is considered as valid to the extent that researchers are able to address the ideas which they set out to study. Consequently, validity can be described as the credibility and accuracy of a study (Bailey, 1991). Internal validity measures the extent to which an independent variable causes a change in the dependent variable. External validity measures the extent to which the data or ideas generated are applicable to other populations, settings or treatments. External validity is about the generalizability of the findings (Thomas & Nelson, 1990). External validity is linked to ecological validity because the latter is related to how closely the data and the experiment reflect the real world or natural setting (George, Batterham, & Sullivan, 2003). External validity will not be an issue for this study because secondary data will be used for this study and the study results will not be generalizable (George et al., 2003). Scholars using secondary data collected for other purposes must be concerned with its quality and potential biases (Bevan, Baumgartner, Johnson, & McCarthy, 2013). A threat to internal validity is the reliance on previously conducted survey estimates regarding historic EHR data. However, this may not pose a validity threat to history or maturation because a purpose convenience sampling approach, which features reasonable cost and time parameters will be used (Bevan et al., 2013; Cunningham, & McCrum-Gardner, 2007). The use of secondary data sources for this study also make validity threats to testing and instrumentation irrelevant because this study will not involve human subjects (Karras, 1997; Thomas & Nelson, 1990). Similarly, threats due to selection bias, experimental mortality and expectancy will be non-existent because this study will use secondary data, which will not involve human subjects (Karras, 1997). Threat to internal validity due to statistical regression will not be a factor in this study because the values of comparison groups selected as extremes for a score will not be impacted by multiple tests, which would have been the case after a treatment intervention with human subjects (George, Batterham, & Sullivan, 2003).

Content validity will be a major validity limitation because there will be no independent way to verify the information provided by the survey participants, to account for the differences in how each organization operates and the reporting tool may not reflect these variations (Bevan et al., 2013). It will also be impossible to determine the extent to which management and operational actions will be reflected when answering the questions to the survey. Another possible threat to internal validity is data collection bias. Since both HIMSS and AHA conduct surveys, the results of those studies may have been biased; for example, Physicians who already used EHRs, "early adopters," would be more likely to respond to inquiries about software applications and other systems, but nonusers are likely to guess or not provide answers and this could leave gaps in the data (Ford, Menachemi, & Phillips, 2006). Respondents to the previous surveys may have provided answers to questions, which may be inconsistent from year to year and such changes are not likely to be detected. A third potential source of bias lies in how EHRs were defined in previous studies (Ford, Menachemi, & Phillips, 2006). Respondents may have viewed their nonclinical automated systems (i.e., electronic scheduling and billing) as EHRs. Moreover, users of less robust systems may have responded positively despite the fact that key capabilities of a minimal EHR may not have been present (Ford, Menachemi, & Phillips, 2006). All these biases may result in data errors which cannot be detected.

Data errors can skew the outcomes of research studies. Large-scale electronic health record research introduces biases compared to traditional research (Hoffman, & Podgurski, 2013). A small number of errors can have “a relatively large effect” on internal validity (Hripcsak, Knirsch, Zhou, Wilcox, & Melton, 2011). Data errors that do not occur at random are especially problematic because they may systematically bias research outcomes (Greenland, 2005). Incomplete or fragmented data may also compromise the reliability of EHR database information. At times, EHR data does not include all of the information needed for particular research projects (Newgard, Zive, Jui, Weathers, & Daya, 2012). The above limitations can be addressed by using accepted statistical approaches and national sampling methodologies (Ford, Menachemi, & Phillips, 2006). Through a process of continued critical evaluation and additional research, plausible threats to validity can be identified and eliminated, yielding improved estimates of the causal effect (West, Duan, Pequegnat, Gaist, Des Jarlais, Holtgrave, & Mullen, 2008).

To ensure data integrity and reliability, AHA generates estimates from the previous year's responses, and from comparisons to hospitals of similar size and orientation to account for missing data (AHA Data Collection Methods, n.d.). AHA investigates unusual changes in in year to year data by looking for explanations in other responses or by contacting the hospitals directly for clarification (AHA Data Collection

Methods, n.d.). To assure meaning data, AHA aggregates responses by hospital type, size and geographic area, and compares answers to response from prior periods. Any discrepancies with historic trends require reexamination of individual cases until either the reported data are validated or specific problems are identified (AHA Data Collection Methods, n.d.). The Dorenfest Institute for Health Information which is an innovative online resource that helps meet the academic and global demand for healthcare information technology data to improve patients care also takes similar steps to ensure the integrity of its data. For this study, I will obtain secondary data from AHA and HIMSS Dorenfest Institute; I will establish follow up procedures with contact persons, in these organizations, from whom I will seek clarification of inconsistent or missing data.

Ethical Procedures

Agreements for data access and study analysis will be completed prior to the actual access of the data. All ethical procedures will be addressed through the study, also having an external review by the Institutional Review Board (IRB; Walden University, 2015). IRB review will ensure that the study does not pose any validity or ethical concerns with the study's methods or procedures. Any ethical concerns regarding human subjects, deception or invasion of privacy will not apply in this study because secondary data sources will be used for this study. The confidentiality of all results was maintained by blinding the identifier for the participating hospitals; only results will be available.

The secondary data obtained from HIMSS and AHA will keep the identity of the participants anonymous. No attempts will be made to identify the study participants because any attempt to identify individuals that participated in this study will violate the terms and conditions of the agreements with HIMSS and AHA. Confidentiality of the participants in the survey will remain the responsibility HIMSS and AHA. Since the survey participants will not be identified, there will be no requirement to destroy data to maintain anonymity of the study participants.

This study will be subject to review process by the Institutional Review Board (IRB) at Walden University. The IRB review the data collection method for primary research, sensitive topics such as legal or illegal proceedings, and use of vulnerable populations. This study will not contain any of the immediate high-risk areas; however, the IRB will still review the plan for the study prior to data exchange from the data source. Statistical analysis with software such as SPSS will allow the participants' information to be entered and stored with confidentiality and participants will be identified only by a case number. The exchange of data will be done through an encrypted, secure (password protected) email method with storage encryption. The information will then be securely encrypted and backed up on the platform of the software download. The information and details of the survey results will also be destroyed following the (statistical analysis) and final approval for the doctoral degree.

Summary

DesRoches et al. (2013) concluded that the meaningful use incentive program has been successful at increasing the number of hospitals pursuing comprehensive EHR adoption on the basis of the $27.3 billion investment in the Medicare and Medicaid EHR Incentive program, between 2011 and 2016, by the U.S government. Researchers have raised concerns about the quality of EHR data for the coding, tracking and recording of medical information for patients (Haghighi, Dehghani, Teshizi & Mahmoodi, 2013; Paul & Robinson, 2012). The importance of the demonstration of MU validates the need to investigate circumstances that influence how providers demonstrate MU by focusing on hospital demographics and EHR software application attributes to measure Stage 1 Meaningful Use (MU) objectives (Shea, Reiter, Weaver, Thornhill & Malone, 2015). The aim of this study is to produce information about the effects of hospital attributes on EHR implementation.

The research design that will be used for this study will be a correlational quantitative and cross-sectional design. This type of research design is commonly used to describe the pattern of relation between variables for secondary data (Field, 2013). Secondary data will be obtained from the Health Information and Management Systems Society (HIMSS) Analytics Databases of nonfederal acute care hospitals in the United (HIMSS Foundation, n.d. A), and the American Hospital Association (AHA) Annual Survey Database (AHA Data Viewer, 2014). The secondary data sources used for this study have been used to conduct a number of studies and are highly regarded for their integrity and reliability (Furukawa et al., 2010; Jones et al., 2014; McCullough et al., 2010; Miller & Tucker 2011; Appari et al. 2012). This research design was chosen because it will allow the study to produce information about the selected variables and could potentially help policy makers, health systems, and practice leaders tailor policies and allocate resources effectively and to support providers in practice settings that may otherwise not able to demonstrate MU. To compensate for the limitations of cross-sectional evaluation design and correlational analyses, statistical analyses will be used to calculate the relationship between the dependent and independent variables.

The sample will be a purposive convenience sample which will represent all hospitals that reported. The power analysis results indicate that data from 174 hospitals should be included (see below); however, all cases in the secondary data source will be used. The data will be analyzed through correlation analysis and multiple linear regression analysis to address the statistical predictive relationship between hospital attributes and EHR software application attributes, and to address the statistical predictive relationship between EHR software application attributes and the successful implementation of Stage 1 Meaningful Use. These models of data are most suitable for describing the relationship between dependent variables and one or more independent variables (Laerd Statistics, 2013).

Chapter 4: Results

Introduction

My purpose in conducting this study was to analyze the relationship between EHR attributes and their relationship to the Stage 1 MU implementation process. To the extent that MU impacts care delivery, demonstration of MU may have an impact on evaluating the care offered to Medicare and Medicaid patients (Shea et al., 2015). In light of the renewed efforts by the U.S. government to encourage use of EHRs for upgrading delivery of care and public health, it is necessary to analyze the circumstances that impact how providers demonstrate MU by focusing on EHR software application attributes and hospital demographics to measure Stage 1 MU objectives (Shea et al., 2015). I wanted to produce information about the relationships between hospital attributes and EHR implementation, which may help policy makers, health system administrators, and practice leaders tailor policies and allocate resources effectively, and support providers in practice settings that may otherwise not able to demonstrate MU.

Research Question and Hypotheses

RQ 1 – What is the predictive relationship between hospital attributes (facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented? (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status?

Null Hypothesis 1 (H_01): There is no statistically predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status.

Alternative Hypothesis 1 (H_A1): There is a statistically significant predictive relationship between hospital attributes (hospital facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status.

RQ 2 – What is the predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status and successful implementation of Stage 1 MU objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information)?

Null Hypothesis 2 (H_02): There is no statistically significant predictive relationship between EHR software application attributes implemented

(Cardiology Information System, Health Information Management System - Electronic Forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE status and successful implementation of Stage 1 Meaningful Use (MU) objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Alternative Hypothesis 2 (H_A2): There is a statistically significant predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE status and successful implementation of Stage 1 MU objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information).

Data Collection

HIMSS staffers follow an annual process in updating the organization's database. This process involves initial data gathering conducted by phone followed by an IT inventory survey completed by hospital administrators (HIMSS, n.d.). The Dorenfest Institute provides detailed historical data, reports, and white papers about IT use in hospitals and integrated health care delivery networks to universities, students under university license, U.S. governments (local, state and federal), and governments of other countries that will be using the data for research purposes (HIMSS, Analytics, 2016). The HIMSS database included a total of 5,467 hospitals in the United States and District of Columbia. The population of interest for this study was nonfederal hospitals in the northeast region of the United States.

As part of the data cleaning processing, I reviewed the Microsoft Access tables, which contained the data, to determine which ones housed that relevant data for this study. I sorted the tables in ascending order, using the Entity ID as a primary key. I extracted the columns that contained the independent and dependent variables and combined the respective data into one table and exported the file into a Microsoft Excel spreadsheet. A review of the data showed that each occurrence of the independent and dependent variable was recorded at the entity level. The review also showed that entities reported results for multiple locations with different number of staffed beds within the same state. The relationships between Entity IDs, Entity Type, Location, Organizational Control, and Number of Staffed Beds to their corresponding applications and functions resulted in multiple cases of each of the hospital attributes. In order to account for the unique instances of the actual number of entities and their corresponding variables, I removed the duplicate records using Entity IDs and Number of Staffed Beds.

Discrepancies in Data Collection Plan

The data design and groupings of the variables for this study were based on the descriptions contained in the data dictionary provided by the Dorenfest Institute. However, there were discrepancies in the actual file structure that I downloaded. For ethical reasons, I did not access the database until after I had gained final approval from the IRB when I detected discrepancies between the structure of the actual data and what I anticipated in my initial design. The column labeled Organizational Control contained an additional variable called Profit Status so I moved that variable into a separate column. A detailed breakdown of the revised coding for all the variables is provided in Appendix H. My initial estimate of the sample size was 174 hospitals based on the G-Power analysis. However, only 83 hospitals reported survey results for the North East region of United States. As a result, I included 86 hospitals from the Mid-Atlantic region to bring the total sample size to 169 after obtaining approval to add the additional region from the Walden IRB. The overall impact in the discrepancy in the sample size was minimal because the focus of the study was to evaluate the relationship between the independent and dependent variables, and each hospital provided detailed instances of the variables to allow for meaningful analysis.

Table 6

Power Calculations for Each EHR Software Applications Attribute Dependent Variable Using Four Predictor Variables, Effect Size Calculated with R^2, and Alpha of .05

Dependent Variables	*N*	R^2	Effect Size	Power (error probability)
EHR Software Application Attributes (CDSS Components)	169	.102 (10.2%)	.3	.992
EHR Software Application Attributes (CDSS Components)	169	.102 (10.2%)	.3	.992
Successful Implementation of MU	169	.102 (10.2%)	.3	.992

Sample Demographics Compared to Population

Demographic representation of the sample comprised 169 hospitals in the North-East Region and Mid-Atlantic regions of the United States. The sample is representative of the hospitals with number of staffed beds between 50 and 1,000 in the North East and Mid-Atlantic regions of the United States. A purposive convenience sample method, which represented all hospitals that reported, was included in the data set.

The demographics of the respondents were divided into four main categories: Hospital Region, Ownership Status, Number of Staffed Beds, and Organizational Control. The first category included demographics related to hospitals located in the North East and Mid-Atlantic regions of the Unites States which are shown in Table 7. Region 1 was represented by Maine, New Hampshire, Connecticut, Massachusetts, Vermont, Rhode Island, Delaware, New Jersey, New York and Pennsylvania which reported 49% of the reported cases for 83 hospitals. Region 2 included Maryland, District of Columbia, Virginia, West Virginia, North Carolina and Kentucky which reported 51% of the reported cases for 86 hospitals. Table 7 list demographics of the independent and dependent variables for this study.

Table 7

Demographics of the Independent and Dependent Variables

Independent Variables

Name / Description	Frequency	Percentage
Region		
Region – 1 (ME, NH, MA, CT, VT, RI, NY, NJ, PA)	83	49
Region – 2 (MD, WV, VA, DC, NC, KY)	86	51
Total Organizations *(N)*	169	
Ownership Status		
Managed Hospitals	16	10
Owned Hospitals	153	90
Total Organizations *(N)*	169	

Number of Staffed Beds		
Beds <= 250	117	69
≥ 250	52	31
Total Organizations *(N)*	169	
Organizational Control		
Government, non-federal	23	14
Non-Government, non-for-profit	146	86
Total Organizations *(N)*	169	
Dependent Variables *(N = 169)*		
	M	SD
EHR Software Application Attributes (CDSS Components)	318	160
EHR Software Application Attributes (Major Systems)	292	178
Successful Implementation of Meaningful Use	349	213

Results

Statistical analyses were conducted using the Statistical Package for Social Sciences (SPSS) Version 24.0 software. Using the Explore feature in SPSS, the file was examined for missing data and it was determined that the missing data were a random subset of the data and there was no relationship between whether a data point is missing and any values in the data set, missing or observed; the data was missing completely at random (MCAR) (Osborne, 2011; Pigott, 2001). A total of 169 hospitals were used to run the analyses.

Correlations

The correlations between variables were examined by using the Pearson's Correlation Coefficient Tests in SPSS. This was completed to determine if any variables (predictor or criterion) were highly correlated (multicollinearity). According to Field (2013), if any of the variables shows a high Pearson's Correlation Coefficient (r < +/-) of .08 or higher, one of the variables should be removed from the regression testing in order to not confound the results. During this testing, all of the variables for each of the criterion variables with the predictor variables were compared. Results indicate that none of the variables had a high correlation coefficient. The range for all the variables was (-.153 < R > .207). Table 8 summarizes the results of the correlation testing or all variables and the results of the complete correlation testing can be found in detail in Appendix D.

Table 8

Statistically Significant Results or Pearson's Correlation Coefficient Testing Between Variables

	Variable	Pearson's Correlation	Sig p-value (2-tailed)
Region			
	EHR Software Application Attributes (CDSS Components)	.207**	.007
	EHR Software Application Attributes (Major Systems)	.186*	.015
	Successful Implementation of MU	.184*	.016
Ownership Status			
	EHR Software Application Attributes (CDSS Components)	-.113	.145
	EHR Software Application Attributes (Major Systems)	-.102	.188
	Successful Implementation of MU	-.103	.183
Number of Staffed Beds (Size)			
	EHR Software Application Attributes (CDSS Components)	.144	.062
	EHR Software Application Attributes (Major Systems)	.175*	.023
	Successful Implementation of MU	.172*	.025
Organizational Control			
	EHR Software Application Attributes (CDSS Components)	-.163*	.034
	EHR Software Application Attributes (Major Systems)	-.152*	.048
	Successful Implementation of MU	-.153*	.047

** Correlation is statistically significant to the $p < .01$ level (2-tailed)
* Correlation is statistically significant to the $p < .05$ level (2-tailed)

t-Tests

T-tests were performed to determine the differences in the means between two groups of the same variable and to compute the standard error for variability between sample means (Field, 2013). Each of the independent variable values were categorized into two groups. Region was categorized into Region 1 (ME, NH, MA, CT, VT, RI, NY, NJ, PA), and Region 2 (MD, WV, VA, DC, NC, KY), and Number of Staffed Beds was grouped by Beds ≥ 250 and Beds ≤ 250. T-test analyses were completed to determine if there were statistically significant mean differences between groups in the dependent variable. The first t-test compared the mean for EHR Software Application Attributes (CDSS Components) for Region 1 and Region 2. The second t-test compared the mean for EHR Software Application Attributes (Major Systems) for Region 1 and Region 2. The third t-test compared the mean for Successful Implementation of MU. Similar tests were conducted to compare the means for Number of Staffed Beds, Ownership Status and Organizational Control.

Assumptions. There were six assumptions for the t-tests. The first assumption was that the **dependent variable** was measured on a **continuous scale** and this assumption was met. The level of measurement in the Variable View in SPSS classified the type of data for the dependent variables as scale and the boxplot histograms for the dependent variables (shown in Apendix C) also affirm scale continuity. The second assumption was that each of the four **independent variables** should consist of **two categorical, independent groups and this assumption was also met**. The independent variable of Region comprised hospitals in Region 1 and Region 2. The variable of Ownership Status was categorized into two groups: Managed and Owned; Number of Staffed Beds consisted of hospitals with ≤ 250 Staffed Beds and entities with ≥ 250 Staffed Beds. Organizational Control was made up of hospitals that were Government, non-federal and Non-Government--non-for-profit. These two assumptions are addressed in Table 9 which identifies the levels of measurements for the independent and dependent variables assigned by SPSS. Appendix F shows the boxplot histograms for the dependent variables.

Table 9

SPSS Classification of Dependent Variables in Variable View

Label	Values	Level of Measurement
Region IV1	Region 1 ; Region 2	Nominal
Ownership Status IV2	Managed and Owned	Nominal
Number of Staffed Beds (Size) IV3	≤ 250 ; ≥ 250	Nominal
Organizational Control IV4	Government, non-federal ; Non-Government, non-for-profit	Nominal
EHR Software Applications Attributes (CDSS Components) DV1	None	Scale
EHR Software Applications Attributes (Major Components) DV2	None	Scale
Successful Implementation of MU DV3	None	Scale

The third assumption was for independence of observations, which means that there was no relationship between the observations in each group or between the groups themselves. There were no relationships between hospital region, ownership status, number of staffed beds and organizational control; each of the attribute was independent of the others. The fourth assumption was that there should be no significant outliers. This assumption was validated by the details of the scatter plots provided in Appendix C, which indicate a linear relationship between the independent and dependent variables and shows minimal outliers. The fifth assumption was for the dependent variable to be approximately normally distributed for each group of the independent variable. Assumptions four and five were met as demonstrated by the Normal Q-Q Plots of the dependent variables in Appendix C. The sixth assumption was for homogeneity of variances for which the Levene's test for homogeneity of variances was used (assumption test results can be found in Appendix E). The following section presents a table for each independent variable and discusses the statistically significant differences of that analysis. Table 10 - 13 provide results of the t-tests for each of the independent variables. The results of the Q-Q Plots and de-trended Q-Q Plots provided in Appendix C address the fourth assumption and results of the Tests of Normality address the fifth assumption.

Region. Table 10 shows the means for the independent variable of Region, which is subdivided into Region 1 which comprises hospitals in ME, NH, MA, CT, VT, RI, NY, NJ, PA and Region 2 which includes hospitals in MD, WV, VA, DC, NC, KY with EHR Software Application Attributes (CDSS Components). Levene's Test for Equality of Variances demonstrated that the differences are not statistically significant ($p > .05$) and we can assume equal variances. The t-tests for the predictor variable of Region and the criterion variable of EHR Software Application Attributes (CDSS Components), Region 1 ($M = 285.05$, $SE = 17.752$) compare to Region 2 ($M = 351.16$, $SE = 16.440$), with a difference of means, -66.115, was statistically significant, $t(167) = -2.735$, $p = .007$. The t-tests for the predictor variable of Region and the criterion variable of EHR Software

Application Attributes (Major Systems), Region 1 (M = 258.08, SE = 19.417) compare to Region 2 (M = 323.98, SE = 18.679), with a difference of means, -65.892, was statistically significant, t(167) = -2.447, p = .015. The t-tests for the predictor variable of Region and the criterion variable of Successful Implementation of MU, Region 1 (M = 309.70, SE = 23.239) compare to Region 2 (M = 387.90, SE = 22.402), with a difference of means, -78.197, was statistically significant, t(167) = -2.423, p = .016.

Table 10

Means for the Independent Variable of Region

	Region		Difference In Means	Sig. (2-tailed)
	Region1	Region2		
EHR Software Application Attributes (CDSS Components)	285.05	351.16	-66.115	.007
EHR Software Application Attributes (Major Systems)	258.08	323.98	-65.892	.015
Successful Implementation of MU	309.70	387.90	-78.197	.016

Ownership Status. Table 12 contains the independent variable of Ownership Status, which is subdivided into Managed Hospitals and group two being Owned Hospitals with EHR Software Application Attributes (CDSS Components), and results of the t-tests on the dependent variable. Levene's Test for Equality of Variances demonstrated that the variances are not statistically significant (p > .05) and we can assume equal variances. The t-tests for the predictor variable of Ownership Status and the criterion variable of EHR Software Application Attributes (CDSS Components), Managed Hospitals (M = 374.25, SE = 41.018) compare to Owned Hospitals (M = 312.88, SE = 12.861), with a difference of means, 61.368, was not statistically significant, t(167) = 1.464, p = .145. The t-tests for the predictor variable of Ownership Status and the criterion variable of EHR Software Application Attributes (Major Systems), Managed Hospitals (M = 347.38, SE = 44.533) compare to Owned Hospitals (M = 285.78, SE = 14.320), with a difference of means, 61.591, was not statistically significant, t(167) = 1.323, p = .188. The t-tests for the predictor variable of Ownership Status and the criterion variable of Successful Implementation of MU, Managed Hospitals (M = 416.94, SE = 53.398) compare to Owned Hospitals (M = 342.44, SE = 17.147), with a difference of means, 74.500, was not statistically significant, t(167) = 1.336, p = .183.

Table 11

Means for the Independent Variable of Ownership Status

	Ownership Status		Difference In Means	Sig. (2-tailed)
	Managed	Owned		
EHR Software Application Attributes (CDSS Components)	374.25	312.88	61.368	.145
EHR Software Application Attributes (Major Systems)	347.38	285.78	61.591	.188
Successful Implementation of MU	416.94	342.44	74.500	.183

Number of Staffed Beds (Size). Table 13 contains the means for the independent variable of Number of Staffed Beds, which is subdivided into hospitals with ≥ 250 beds and hospitals with ≤ 250 beds. Levene's Test for Equality of Variances demonstrated that the variances are not statistically significant (p > .05) and we can assume equal variances. The t-tests for the predictor variable of Number of Staffed Beds (size) and the criterion variable of EHR Software Application Attributes (CDSS Components), Number of

Staffed Beds (size) ≤ 250 (M = 303.39, SE = 14.885) compare to Number of Staffed Beds (Size) ≥ 250 (M = 353.12, SE = 21.350), with a difference of means, -49.722, was statistically significant, t(167) = -1.878, p = .062. The t-tests for the predictor variable of Number of Staffed Beds (size) and the criterion variable of EHR Software Application Attributes (Major Systems), Number of Staffed Beds (size) ≤ 250 (M = 270.97, SE = 16.340) compare to Number of Staffed Beds (Size) ≥ 250 (M = 338.08, SE = 23.892), with a difference of means, -67.111, was statistically significant, t(167) = -2.296, p = .023. The t-tests for the predictor variable of Number of Staffed Beds (size) and the criterion variable of Successful Implementation of MU, Number of Staffed Beds (size) ≤ 250 (M = 325.12, SE = 19.591) compare to Number of Staffed Beds (Size) ≥ 250 (M = 404.33, SE = 28.589), with a difference of means, -79.207, was statistically significant (t(167) = -2.261, p = .025).

Table 12

Means for the Independent Variable of Number of Staffed Beds (Size)

	Number of Staffed Beds (Size)		Difference In Means	Sig. (2-tailed)
	≤ 250	≥ 250		
EHR Software Application Attributes (CDSS Components)	303.39	353.12	-49.722	.062
EHR Software Application Attributes (Major Systems)	270.97	338.08	-67.111	.023
Successful Implementation of MU	325.12	404.33	-79.207	.025

Organizational Control. Table 14 identified the means for the independent variable of Organizational Control, which is subdivided into Government, non-federal hospitals and Non-Government, non-for-profit (NFP). Levene's Test for Equality of Variances demonstrated that the variances are not statistically significant (p > .05) and we can assume equal variances.

The t-tests for the predictor variable of Organizational Control and the criterion variable of EHR Software Application Attributes (CDSS Components), Government, non-federal hospitals (NFP) (M = 384.35, SE = 35.988) compare to Non-Government, non-for-profit (NFP) (M = 308.35.12, SE = 12.922), with a difference of means, -49.722, was statistically significant, t(167) = 2.139, p = .034. The t-tests for the predictor variable of Organizational Control and the criterion variable of EHR Software Application Attributes (Major Systems), Government, non-federal (M = 359.57, SE = 38.311) compare to Non-Government, non-for-profit (NFP) (M = 280.91, SE = 14.473), with a difference of means, -78.654, was statistically significant, t(167) = 1.991, p = .048. The t-tests for the predictor variable of Organizational Control and the criterion variable of Successful Implementation of MU, Government, non-federal hospitals (M = 431.13, SE = 46.033) compare to Non-Government, non-for-profit (NFP) (M = 336.63, SE = 17.323), with a difference of means, -94.500, was statistically significant, t(167) = 1.998, p = .047.

Table 13

Means for the Independent Variable of Organizational Control

	Organizational Control		Difference In Means	Sig. (2-tailed)
	Govt., non-federal	Non-Govt., (NFP)		
EHR Software Application Attributes (CDSS Components)	384.35	308.35	75.999	.034

EHR Software Application Attributes (Major Systems)	359.57	280.91	78.654	.048
Successful Implementation of MU	431.13	336.63	94.500	.047

Research Question 1

Multiple linear regression. Multiple linear regression for each of the dependent variables for research question 1 were run using a forced entry ("Enter") model. The forced entry model was chosen because there was low/no multicollinearity (all variables were kept in the model in the model) and each of the predictor variables was of equal influence on the dependent variables (Field, 2013). Each multiple linear regression was conducted to evaluate how well the predictor variables: Region, Ownership Status, Number of Staffed Beds (Size), and Organizational Control predicted the dependent variables: EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU.

Assumptions. Linear regression has five key assumptions: First, linear regression requires a linear relationship between the independent and dependent variables and for outliers to be verified (Osborne, Christensen, & Gunter April, 2001). The linearity assumption can best be tested with scatter plots (Field, 2013). This assumption was validated by the details of the scatter plots provided in Appendix C, which indicate a linear relationship between the independent and dependent variables and shows minimal outliers. Second, the linear regression analysis requires all variables to be multivariate normal. This assumption was established by the histograms and Q-Q-Plots demonstrated in Appendix C. Normality was established with the Kolmogorov-Smirnov goodness of fit test (Osborne, Christensen & Gunter April, 2001). Table 15 shows the Kolmogorov-Smirnov goodness of fit test for the dependent variables.

Table 14

Tests of Normality

Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
EHR Software Application Attributes (CDSS Components)	.130	169	.000	.939	169	.000
EHR Software Application Attributes (Major Systems)	.170	169	.000	.892	169	.000
Successful Implementation of MU	.171	169	.000	.892	169	.000

a. Lilliefors Significance Correction

Third, linear regression assumes that there is little or no multicollinearity in the data. Multicollinearity occurs when the independent variables are too highly correlated with each other and may be tested with Tolerance (Pedhazur, 1997), which measures the influence of one independent variable on all other independent variables. Tolerance is calculated with the Variance Inflation Factor (VIF, where a VIF of < 5 indicates no multicollinearity among the variables (Pedhazur, 1997). The results of the multicollinearity test, which are shown in Appendix G, established that there were no concerns of multicollinearity and the relative importance of the independent variables in explaining the variation caused by the dependent variable can be determined. The last assumption of the linear regression analysis is homoscedasticity (Field, 2013). The scatter plot is good way to check whether the data is homoscedastic, or if the residuals are equal across the regression line (Cohen, & Cohen, 1983). The results of the homoscedasticity test, shown in Appendix C, validated that the residuals were equal across the regression line.

Common findings for all Dependent Variables. The results indicated, after data cleaning, that there were N = 169 EHR Software Application Attributes (CDSS Components), N = 169 EHR Software Application Attributes (Major Systems), and N = 169 Successful Implementation of MU. The predictors for all of the dependent variables were the four hospital attributes and the criterions (dependent variables) were EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU. The model summary indicated a statistically significant relationship between the four independent variables and the outcomes of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU, when combined (p = .001).

EHR Software Application Attributes (CDSS Components) (Dependent Variable). The R^2 (R^2 = .102) for the linear regression and the correlation coefficient (R) was .319 indicated that only approximately 10.2% of the variable of outcome occurrences in the sample can be accounted for by the linear combination of the predictors. The linear combination of the predictors was statistically significant as compared to the outcome of EHR Software Application Attributes (CDSS Components) occurrences, F(4, 164) = 4.657, p = .001. Table 16 shows the detail of the coefficient analysis for EHR Software Application Attributes (CDSS Components).

Table 15

Model 1 Multiple Linear Regression Coefficient Analyses for EHR Software Application Attributes (CDSS Components)

Coefficients	*B*	*SE*	Beta
Constant*	427.121	143.309	
Region	60. 621	24.699	.190
Ownership Status	-64.879	41.134	-.119
Number of Staffed Beds (Size)	69.353	26.196	.201
Organizational Control	-58.303	35.629	-.125

*Model 1 with R^2 = .102 with p = .001

EHR Software Application Attributes (Major Systems) (Dependent Variable). The R^2 (R^2 = .102) for the linear regression and the correlation coefficient (R) was .320 indicated that only approximately 10.2% of the variable of outcome occurrences in the sample can be accounted for by the linear combination of the predictors. The linear combination of the predictors was statistically significant as compared to the outcome of EHR Software Application Attributes (Major Systems) occurrences, $F(4, 164) = 4.681$, p = .001. Table 17 includes the detail of the coefficient analysis for EHR Software Application Attributes (Major Systems).

Table 16

Model 1 Multiple Linear Regression Coefficient Analyses for EHR Software Application Attributes (Major Systems)

Coefficients	*B*	*SE*	Beta
Constant*	394.721	158.965	
Region	61.763	27.397	.174
Ownership Status	-69.610	45.628	-.115
Number of Staffed Beds (Size)	87.659	29.058	.228
Organizational Control	-62.257	39.521	-.121

*Model 1 with R^2 = .102 with p = .001

Successful Implementation of MU (Dependent Variable. The R^2 (R^2 = .101) for the linear regression and the correlation coefficient (R) was .318 indicated that approximately 10.1% of the variable of outcome occurrences in the sample can be accounted for by the linear combination of the predictors. The linear combination of the predictors was statistically significant as compared to the outcome of Successful Implementation of MU occurrences, $F(4, 164) = 4.610$, $p = .001$. Table 18 includes the detail of the coefficient analysis for Successful Implementation of MU.

Table 17

Model 1 Multiple Linear Regression Coefficient Analyses for Successful Implementation of MU

Coefficients	*B*	*SE*	Beta
Constant*	478.673	190.539	
Region	72.964	32.839	.172
Ownership Status	-83.941	54.691	-.116
Number of Staffed Beds (Size)	103.756	34.829	.226
Organizational Control	-75.080	47.371	-.121

*Model 1 with $R^2 = .101$ with $p = .001$

The statistically significant results are indicated for EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU. These outcomes are statistically significant at the $p < .05$ level ($p = .001$). A summary of the results of the multiple regression analyses for all the criterions (dependent variables) is provided in Table 19. The information presented was discussed in further detail for each specific criterion variable. It is presented in this chapter with complete results in Appendix F.

Table 18

Model 1 Multiple Linear Regression Analyses for the Criterion Variable

Dependent Variables	*R*	*R^2* (% contributed)*	*df*	*F*	*Sig (p value)*
EHR Software Application Attributes (CDSS Components)	.319	.102 (10.2%)	4, 164	4.657	.001**
EHR Software Application	.320	.102 (10.2%)	4, 164	4.681	.001**

Attributes (Major Systems)					
Successful Implementation of MU	.318	.101 (10.1%)	4, 164	4.610	.001**

*R^2 indicated the use Model 1 for all criterion variables
** Correlation is statistically significant to the p < .05 level (2-tailed)

Research Question 2

Multiple linear regression. Multiple linear regression for each of the dependent variables for RQ 2 were run using a forced entry ("Enter") model. The forced entry model was chosen because there was low/no multicollinearity (all variables were kept in the model in the model) and each of the predictor variables were of equal influence on the dependent variables (Field, 2013). Each multiple linear regression was conducted to evaluate how well the predictor variables: EHR Software Application Attributes (Major Systems) and EHR Software Application Attributes (CDSS Components) predicted the dependent variables: Successful Implementation of MU. These tests were run using the same linear regression assumptions used for RQ 1. The results of the assumptions are provided in Table 20. Detailed results of the assumptions are provided in Appendix L.

Assumptions. Linear regression has five key assumptions: First, linear regression requires a linear relationship between the independent and dependent variables and for outliers to be verified (Osborne, Christensen & Gunter April, 2001). The linearity assumption can best be tested with scatter plots (Field, 2013). The details of the scatter plots for the dependent variables are provided in Appendix C. Second, the linear regression analysis requires all variables to be multivariate normal. This assumption can best be checked with a histogram or a Q-Q-Plot and normality can be checked with the Kolmogorov-Smirnov goodness of fit test (Osborne, Christensen & Gunter April, 2001).

Table 20 shows the Kolmogorov-Smirnov goodness of fit test for the dependent variables. Details of Q-Q-Plot are provided in Appendix L.

Table 19

Tests of Normality

Variables	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Successful Implementation of MU	.171	169	.000	.892	169	.000

a. Lilliefors Significance Correction

Third, linear regression assumes that there is little or no multicollinearity in the data. Multicollinearity occurs when the independent variables are too highly correlated with each other and may be tested with Tolerance (Pedhazur, 1997). Tolerance measures the influence of one independent variable on all other independent variables. Tolerance is calculated with the Variance Inflation Factor (VIF, where a VIF of < 5 indicates no multicollinearity among the variables (Pedhazur, 1997). The results of the multicollinearity test are shown in Appendix K. The last assumption of the linear regression analysis is homoscedasticity (Field, 2013). The scatter plot is good way to check whether the data is homoscedastic, or if the residuals are equal across the regression line (Cohen, & Cohen, 1983). The results of the homoscedasticity test are shown in Appendix C. A summary of the results of the multiple regression analyses is provided in Table 21 which represents the results of the multiple linear regression analysis for Successful Implementation of MU (dependent variable). The information presented was discussed in further detail for each specific criterion variable. It is presented in this chapter with complete results in Appendix J.

Table 20

Model 1 Multiple Linear Regression Analyses for the Criterion Variable

Dependent Variables	*R*	R^2* (% contributed)	*df*	*F*	*Sig (p value)*
Successful Implementation of MU	.999	.999 (99.0%)	2, 166	105,449.6	.001**

*R^2 indicated the use Model 1 for all criterion variables
** Correlation is statistically significant to the p < .05 level (2-tailed)

The statistically significant results are indicated for EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU. These outcomes are statistically significant at the $p <$ .05 level ($p = .001$).

Successful Implementation of MU (Dependent Variable). The results indicate, after data cleaning, that there was an N = 169 Successful Implementation of MU. The predictors were the EHR Software Application Attributes (CDSS Components) and EHR Software Application Attributes (Major Systems), and the criterion (dependent variable) was Successful Implementation of MU. The R^2 ($R^2 = .999$) for the linear regression and the correlation coefficient (R) was .999 and indicated that approximately 99.9% of the variable of outcome occurrences in the sample can be accounted for by the linear combination of the predictors. The linear combination of the predictors was statistically significant as compared to the outcome of Successful Implementation of MU occurrences, $F(2, 166) = 105{,}449.6$, $p = .001$. The ANOVA for the model indicated that the overall data demonstrated that there was a statistically significant relationship between the two independent variables and the outcome of Successful Implementation of MU when combined) (p = .001). Table 22 includes the detail of the coefficient analysis for Successful Implementation of MU.

Table 21

Model 1 Multiple Linear Regression Coefficient Analyses for Successful Implementation of MU

Coefficients	*B*	*SE*	Beta
Constant*	-.002	1.349	
EHR Software Application Attributes (CDSS Components)	.006	.017	.006
EHR Software Application Attributes (Major Systems)	1.192	.015	.995

*Model 1 with R^2 = .999 with p = .001

Summary

In conclusion, the independent samples t-tests which were performed to determine the differences in the means between two groups of the same independent variable and to compute the standard error for variability between sample means indicated that the t-tests for the predictor variable of Region, and the criterion variables compared Region 1 and Region 2 with a difference of means of at least -65.892 and were statistically significant: EHR Software Application Attributes (CDSS Components) t(167) = -2.735, p = .007, EHR Software Application Attributes (Major Systems), t(167) = -2.447, p = .015, Successful Implementation of MU, t(167) = -2.423, p = .016. Similarly, the independent samples t-tests which were performed for Number of Staffed Beds (Size) and Organizational Control compared their subgroups with a difference of means of, at least, -49.722 and were statistically significant. However, the independent samples t-tests for the predictor variable, Ownership Status, compared Managed Hospitals and Owned Hospitals with a minimum difference of means of 61.368 and was not statistically significant: EHR Software Application Attributes (CDSS Components) t(167) = 1.464, p = .145, EHR Software Application Attributes (Major Systems), t(167) = 1.323, p = .188, Successful Implementation of MU, t(167) = 1.336, p = .183. Overall, the model summary indicated a statistically significant relationship between the independent variables and the outcomes of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU, when combined (p = .001).

The multiple linear regressions for Research Question 1 was conducted to evaluate how well the predictor variables: Region, Ownership Status, Number of Staffed Beds (Size), and Organizational Control predicted the dependent variables: EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU. Overall, the model summary indicated a statistically significant relationship between the four independent variables and the outcomes of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU, when combined (p = .001). The multiple linear regressions for Research Question 2 involved the EHR Software Application Attributes (CDSS Components) and EHR Software Application Attributes (Major Systems) as predictors, and Successful Implementation of MU as the criterion (dependent variable). The linear combination of the predictors was statistically significant as compared to the outcome of Successful Implementation of MU occurrences, $F(2, 166) = 105{,}449.6$, $p = .001$. The ANOVA for the model indicated that the overall data demonstrated that there was a statistically significant relationship between the two independent variables and the outcome of Successful Implementation of MU when combined) ($p = .001$). The next chapter interprets the findings, identifies the limitations of the study, provides recommendations for further research, and describes the implications for positive social change.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

I analyzed EHR attributes and their relationship to the Stage 1 MU implementation process. Known clinical challenges include ensuring that the implementation of EHRs results in better patient care, the minimization of errors, an easier process for locating clinical data and patient records, and improvements in the process for the approval of patient care (Hsieh, as cited by Agno & Guo, 2013). The variables I investigated included region, ownership status, number of staffed beds (size), and organizational control. I investigated the relationship between the variables to determine if there were potential benefits for the national effort to improve the quality of U.S. health care through successful implementation of MU objectives (CMS, 2011).

In analyzing data, I conducted multiple linear regression tests to determine the predictive relationship between EHR software application attributes (CDSS components), EHR software application attributes (major systems), and successful implementation of MU. The null hypotheses were rejected and the alternatives accepted for the overall relationship between the predictors and the outcome variables for the two research questions. Key results for the investigation of the relationship between region, ownership status, number of staffed beds (size), and organizational control were mixed. The independent samples t-tests for region ($t(167) = -2.423$, $p = .016$), number of staffed beds (size) ($t(167) = -2.261$, $p = .025$), and organizational control ($t(167) = 1.998$, $p = .047$) were statistically significant. However, the independent samples t-test results for ownership status ($t(167) = 1.336$, $p = .183$) was not statistically significant.

Overall, the model summary indicated a statistically significant relationship between three of the four independent variables and the outcomes of EHR software application attributes (CDSS components), EHR software application attributes (major systems) and successful implementation of MU, when combined (p = .001). The multiple linear regressions for Research Question 1 suggested a statistically significant relationship between the four independent variables and the outcomes of EHR software application attributes (CDSS components), EHR software application attributes (major systems) and successful implementation of MU, when combined (p = .001). The multiple linear regression result for Research Question 2 included EHR software application attributes (CDSS components) and EHR software application attributes (major systems) as predictors, and successful implementation of MU as the criterion (dependent variable). The linear combination of the predictors was statistically significant as compared to the outcome of successful implementation of MU occurrences, $F(2, 166) = 105{,}449.6$, p = .001. The overall results of the data was a statistically significant relationship between the two independent variables and the outcome of successful implementation of MU when combined (p = .001). The relationship between region, ownership status, number of staffed beds (size), and organizational control was highlighted by the findings.

In this chapter, I further discuss and interpret the results in relation to the research questions. I also consider the limitations of the study, provide recommendations for future studies, and discuss implications for organizations. The chapter also includes recommendations for future research.

Interpretation of the Findings

RQ 1 – What is the predictive relationship between hospital attributes (facility type, organizational control, ownership status, profit status, location/ region, and size) and EHR software application attributes implemented? (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status?

I conducted multiple linear regression for Research Question 1 to evaluate how well the predictor variables of Region, Ownership Status, Number of Staffed Beds (Size), and Organizational Control predicted the dependent variables of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems), and Successful Implementation of MU. Overall, the model summary indicated a statistically significant relationship between the four independent variables and the outcomes of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems), and Successful Implementation of MU, when combined ($p = .001$).

Table 22

Summary Findings for the Overall Hypotheses and Individual Variables – RQ1

Hypotheses	Accept Null (Reject Alternative)	Accept Alternative (Reject Null)	Criterion Significance (p)
EHR Software Application Attributes (CDSS Components)		x	.001**

EHR Software Application Attributes (CDSS Components)	x	.001**
Successful Implementation of MU	x	.001**

**Statistically significant with p <.01.

RQ 2 – What is the predictive relationship between EHR software application attributes implemented (Cardiology Information System, Health Information Management System - electronic forms, Ambulatory EMR System, Utilization Review/Risk Management for Outcomes and Quality Management System, Information Sharing System, and CPOE) status and successful implementation of Stage 1 MU objectives (CPOE, drug-drug and drug-allergy interaction checks, active medication list, record and chart changes in vital signs, and exchange of key clinical information)?

The multiple linear regressions for Research Question 2 involved the EHR Software Application Attributes (CDSS Components) and EHR Software Application Attributes (Major Systems) as predictors, and Successful Implementation of MU as the criterion (dependent variable). The linear combination of the predictors was statistically significant as compared to the outcome of successful implementation of MU occurrences $F(2, 166) = 105{,}449.6$, $p = .001$. The ANOVA for the model indicated that the overall data demonstrated a statistically significant relationship between the two independent variables and the outcome of successful implementation of MU when combined ($p = .001$).

Table 23

Summary Findings for the Overall Hypotheses and Individual Variables – RQ2

Hypotheses	Accept Null (Reject Alternative)	Accept Alternative (Reject Null)	Criterion Significance (p)
Successful Implementation of MU		x	.001**

**Statistically significant with p <.01.

Comparison of Results to Previous Studies

Swindells and de Lusignan (2012) endorsed safety, quality, and efficiency as the overarching goals of health care managers which can be accomplished by leveraging IT. They confirmed the extensive use of IT to support and measure quality of clinical care, clinical consultation and primary care in the form of electronic health records. Vaziri, Connor, Shepherd, Jones, Chan, and de Lusignan (2009) established that IT saves time in issuing medication and improves legibility of prescriptions and records; and drug interactions are flagged in most operational systems, which have enormous potential to prevent errors. I did not investigate the factors researched by Swindells and de Lusignan (2012) and did not have the same focus as Vaziri, Connor, Shepherd, Jones, Chan, and de Lusignan (2009). However, I was able to establish the validity of their assertions and findings by affirming the statistically significant relationships between hospital characteristics, IT systems, and operational processes.

Lehmann and Kim (2006) and Yui, Jim, Chen, Hsu, Liu and Lee (2012) each studied CPOE adoption, highlighted linkages to other health IT, motivated stakeholders, and influence of medical professionals as key factors to successful implementation. Jones, Rudin, Perry, and Shekelle (2014) found that success of CPOE adoption in hospitals depends on the degree to which it is linked to other systems, such as pharmacy, decision-support systems, electronic medical records (EMRs), and electronic medication administration record (e-MAR) systems. I did not scrutinize the human interactions between stakeholders and their systems but one common characteristic between my study and the work of these researchers is the link between the connections between the software application systems that drive the Clinical Decision Support, Electronic Medication Administration, and Electronic Forms Management, Computerized Practitioner Order Entry and Health Information Management processes.

The Centers for Medicare and Medicaid Services (2016B) reported that Hospitals demonstrate Stage 1 Meaningful Use by meeting 14 core objectives, five out of ten menu set objectives, and 15 clinical quality measures (CQMs). The objectives are associated with various outcomes policy priorities designed to improve quality, safety, efficiency and reduce health disparities (Centers for Medicare and Medicaid Services, 2016B). The five core objectives that were selected for inclusion in this study included using computerized provider order entry (CPOE) for medication orders directly entered by any licensed health professional who can enter orders into the medical record per state, local, and professional guidelines; implement drug-drug and drug-allergy interaction checks, maintain active medication allergy list; and record and chart vital signs; height, weight, blood pressure, calculate and display BMI, plot and display growth charts for children 2-20 years, including BMI. I did not employ all the 14 core objectives and all 15 clinical quality measures (CQMs), required by the Centers for Medicare and Medicaid Services to demonstrate Stage 1 Meaningful Use primarily due to the limited scope of this study its limited scope yet my results demonstrated that there was a statistically significant relationship between the two independent variables and the outcome of Successful Implementation of MU when combined) (p = .001).

Findings Related to Theoretical Framework

A number of researchers have studied the extent to which hospital characteristics impact meaningful use for hospitals (Adler-Milstein, DesRoches, Kralovec, Foster, Worzala, Charles, Jha, 2015; Adler-Milstein, Everson, & Lee, 2014; Diana, Harle, Huerta, Ford, & Menachemi, 2014). None of the researchers used NPT or Implementation theory as the framework for their studies so I am unable to compare the outcome of my study with those of previous researchers. I also could not locate any EHR related study that compared EHR software application attributes with the implementation of Stage 1 Meaningful Use objectives nor could I locate any study on meaningful use where the researchers employed the Normalization Process Theory (NPT) and Implementation Theory as the theoretical framework for their research questions. As a result, my interpretation of the findings could not be extended beyond the main features of the theoretical framework.

NPT expresses implementation as a social practice and provides a context for pinpointing factors that impact the routine assimilation of complex interventions by offering a basis for representing varied contexts, structures, social norms, group processes and conventions (Murray et al., 2010). Implementations involving technological, behavioral, and organizational processes are prominent in health care practice but the relationships between their components are unpredictable to evaluate (Campbell et al., 2007). The theory is concentrated on what work needs to be done, by whom, how it is done, and the benefits and costs of the work that is done (May, 2013A; May, 2013B). Implementation theory provides a structure for investigating implementation of complicated interventions and a way to measure and analyze progress and results. Included in the social structures and measurement components of Implementation theory are the various systems and their corresponding attributes that enhance those processes.

The findings of my study are centered on the relationships between hospital attributes and the EHR software applications that allow for Stage 1 MU. I used secondary data which captured only the outcome of the implementations that occurred within the social systems (Bunge, 2004; May, 2013A). I utilized NPT and implementation theory to measure and explain the dynamics within the systems and confirmed a statistically significant predictive relationship between hospital attributes and EHR software application attributes implemented status. I also confirmed that there is a statistically significant predictive relationship between EHR software application attributes implemented status and successful implementation of Stage 1 Meaningful Use (MU) objectives.

Limitations of the Study

The data analysis plan was initially based on the data dictionary provided by the Dorenfest Institute. However, the data file structure that I downloaded was constructed differently than the data dictionary described. For ethical reasons, I did not access the database until after I had gained final approval from the IRB when I detected discrepancies between the structure of the actual data and what I had indicated in my initial design. My initial calculation of needed sample size was 174 hospitals, based on G-Power analysis, but only 83 hospitals reported survey results for North East Region of United States. As a result, after obtaining approval to change my procedures from the Walden IRB, I included 86 hospitals from the Mid Atlantc Region to bring the total sample size to 169. The overall impact in the discrepancy in the sample size was minimal because the gist of the study was to evaluate the relationship between the independent and dependent variables and each hospital provided detailed instances of the variables to allow for meaningful analysis.

Earlier anticipated limitations for the study included reliability and validity of the data collection tool used by the primary data source. Another limitation included restricted reliability and validity testing of the HIMSS surveys prior to the use of such tools (George, Batterham, & Sullivan, 2003). The leaders who completed the assessment tool could have had a bias responding to survey questions about their organization. The plausibility of unconscious bias of management decisions and the impact of those decisions on the social structures and systems involved with the MU implementation processes within the hospitals which provided data for Stage 1 MU objectives measures are other limitations of this study (Hassouneh, 2013).

The final limitation of my study was attributed to my inability to interpret the findings of my study against the backdrop of the full spectrum of my theoretical framework. NPT and implementation theory provide a framework for identifying social structures and electronic systems which integrate and augment the implementation processes used to measure stage 1 MU objectives. The use of secondary data restricted the scope of this measurement to the relationships between the systems but could not address the human interactions involved in these processes.

Recommendations

Medical errors, particularly medication errors, continue to be a troublesome factor in the delivery of safe and effective patient care. The majority of medication errors are associated with breakdowns in poorly defined systems, developing technologies and evolving workflows seem to be a logical approach to provide added safeguards against medication errors (Cronenwett, Bootman, Wolcott, & Aspden, 2007). The medication process in hospitals involves drug procurement, prescribing, dispensing, administering, and monitoring (Cronenwett et, al., 2007). Errors may occur at every step of the medication process even though the majority of them occur during the prescribing and administering stages Berdot et al., 2013). On average, a hospital patient is subjected to more than one medication error each day (McDowell, Ferner, & Ferner, 2009; Cronenwett et al., 2007).

Analyses of cases involving medication errors show that prescribing errors and administration errors are the most commonly reported medication errors in hospitals worldwide (Berdot et al., 2013; Lewis, Dornan, Taylor, Tully, Wass, & Ashcroft, 2009). They are attributed to poorly designed systems and can be addressed by building more robust systems. Like CPOE, medication orders are done electronically and improve clinical decision-making through advice, alerts, and reminders (Institute of Medicine, 2006). Clinical decision-making is enhanced by using a software which matches patient data to a computerized clinical knowledge base to provide patient-specific assessments

(Kuperman, Bobb, Payne, Avery, Gandhi, Burns, & Bates, 2007). Further research is needed in the processes that involve drug dosing interactions, drug interactions, and drug content within the Electronic Medication Administration Record (EMAR) system.

My inability to locate any EHR related study that compared EHR software application attributes with the implementation of Stage 1 Meaningful Use objectives or locate any study on meaningful use that employed the Normalization Process Theory (NPT) and Implementation Theory as the theoretical framework for their research questions offers an opportunity for this study to fill a knowledge gap in the discipline. I recommend that future researchers investigate the various independent variables at a more granular level and cover different regions in the United States.

Implications

The United States government has revitalized efforts to use EHRs for upgrading delivery of care and public health and it is imperative to analyze the conditions that impact how providers demonstrate MU by focusing on EHR software application attributes and hospital demographics to measure Stage 1 Meaningful Use (MU) objectives (Shea, Reiter, Weaver, Thornhill & Malone, 2015). The positive implication of this study is for healthcare clinicians and hospital management to work collaboratively to promote consistent processes that will streamline current processes and meet the Certified Electronic Health Record Technology (CEHRT) standards in order to provide safe, cost-effective and efficient systems for the most optimal patient care. The implications of safe, cost effective and patient centered care are far reaching. The impact to positive social change and implications are further reflected in the recommendations for future practice and study for the health organizations and policy advocates.

Literature/Methodological /Theoretical Implications of this Study

The purpose of this study was to determine the relationship between EHR software application attributes implemented and the extent to which they influence the successful implementation of Stage 1 MU for critical access hospitals. To the extent that MU impacts care delivery, demonstration of MU may have an impact on evaluating the care offered to Medicare and Medicaid patients (Shea et al., 2015). The potential impact of this study to the literature is to add work that applies implementation theory and NPT as theoretical frameworks that can be used to evaluate the implementation of EHR to meet MU objectives.

This study is focused on Stage 1 MU which is one of three stages of the MU incentive program offered by the government. As a consequence, the methodological and theoretical implications highlighted in this study provide opportunities that can be extended to larger studies performed in other parts of the United States. Further study is needed to investigate the attainment of MU objectives at a more robust level using the theoretical framework of the NPT and Implementation theory which offers important perspectives into how new or modified work processes can be routinized in their respective social systems. NPT was developed by researchers who focused on understanding the implementation of advanced and complicated interventions in healthcare settings (McEvoy et al., 2014; May et al., 2007B). It focuses on the treatment of knowledge across professional groups, and aims to understand the implementation of new knowledge by healthcare professionals (Murray, Burns, May, Finch, O'Donnell, Wallace, & Mair, 2011; Gallacher, May, Montori & Mair, 2011).

This framework addresses three major components of NPT which include implementation of work, embedding or translating that work into routine daily processes, and sustaining those processes in their social contexts (May & Finch, 2009). These components provide insights into explaining complex interventions that involve exchanges within a particular situation over time and explain the factors that promote or inhibit the routine embedding of a practice in its social contexts (May & Finch, 2009). These insights will add tremendous value to more advanced studies and advance knowledge in the discipline.

Recommendations for Social Change

I examined the relationships between hospital attributes, EHR application software attributes, and their relationship to the successful implementation of Stage 1 Meaningful Use. I utilized theoretical frameworks that offered a consistent way to evaluate human and system dynamics to explain the implementation of process for the attainment of MU objectives (May, 2013A). I believe that this study offers an alternative approach for hospitals to demonstrate Stage 1 meaningful use which is an important first step in a multiple stage meaningful use demonstration process. CMS mandated in the Stage 1 meaningful use regulations that providers must advance to the Stage 2 criteria after two program years under the Stage 1 criteria which had a core and menu structure for objectives that providers had to achieve in order to demonstrate meaningful use. Although some Stage 1 objectives were either combined or eliminated, most of them are now core objectives under the Stage 2 criteria which are even more stringent. CMS projects that providers who reach Stage 2 in the EHR Incentive Programs will be able to demonstrate meaningful use of their Certified EHR Technology for an even larger portion of their patient populations (Centers for Medicare and Medicaid Services, 2016A).

I recommend that the insight gained from my Stage 1 MU study should be added to existing knowledge in the discipline in order to enable more hospitals to demonstrate meaningful use of their Certified EHR Technology to an ever-increasing patient population. I focused on Stage 1 MU because data was readily available and I was able to use secondary data that was most convenient for the scope of this study. My study was also limited to Critical Access Hospitals in the Northeast and Mid-Atlantic Regions of the United States. As a result, I recommend a more extensive study in other regions of the United States that will use data sources that will make the findings more generalizable.

Conclusion

The U.S. healthcare spending increased to $3.3 trillion and accounted for 17.9% of the nation's Gross Domestic Product in 2016 (Centers for Medicare and Medicaid Services, n.d. A). Over the last several decades, the U.S. government has collaborated with healthcare organizations to improve cost, quality and outcomes; these efforts have not yielded noteworthy results due to political and ideological differences in the U.S. Congress. The Health Information Technology for Economic and Clinical Health (HITECH) Act, enacted as part of the American Recovery and Reinvestment Act of 2009, was signed into law on February 17, 2009, to promote the adoption and meaningful use of health information technology (HealthIT Regulations, n.d).

The Medicare and Medicaid EHR Incentive Programs provide financial incentives for the "meaningful use" of certified EHR technology. To receive an EHR incentive payment, providers have to show that they are “meaningfully using” their certified EHR technology by meeting certain measurement thresholds that range from recording patient information as structured data to exchanging summary care records (HealthIT Regulations, n.d). CMS has established these thresholds for eligible professionals, eligible hospitals, and critical access hospitals. My study examined the relationship between Electronic Health Record Records (EHR) attributes and Stage 1 Meaningful Use (MU) objectives. To the extent that Meaningful Use impacts care delivery, demonstration of MU may have an impact on evaluating the care offered to Medicare and Medicaid patients (Shea et al., 2015). My goal was to produce information about the relationships between hospital attributes and EHR implementation, which may help policy makers, health systems, and practice leaders tailor policies and allocate resources effectively, and support providers in practice settings that may otherwise not able to demonstrate MU.

I evaluated the extent to which the predictor variables: Region, Ownership Status, Number of Staffed Beds (Size), and Organizational Control predicted the dependent variables: EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU and determined a statistically significant relationship between the four independent variables and the outcomes of EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU, when combined (p = .001). I also analyzed the extent to which the predictor variables

EHR Software Application Attributes (CDSS Components) and EHR Software Application Attributes (Major Systems) influenced Successful Implementation of MU and found there was a statistically significant relationship between the two independent variables and the outcome of Successful Implementation of MU when combined) (p = .001). To provide an alternate approach to the investigation of meaningful use, future researches could use NPT and Implementation theory.

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Appendix A: Dorenfest Usage Agreement

Usage Agreement and Application for the Dorenfest Institute for H.I.T. Research and Education Database

1. The Database

The Dorenfest Institute for H.I.T. Research and Education Database includes a variety of detailed historical data about information technology (IT) use in hospitals and integrated delivery networks. This data includes the entire library of Dorenfest 3000+Databases™ and Dorenfest Integrated Healthcare Delivery System Databases™ for the period 1986 through 2003 (hereinafter referred to at the 'Database'), and 2004 through 2009 data from the HIMSS Analytics™ database.

Access to and use of this Database at no charge is restricted to universities, students under university license, and U.S. federal, state, and local governments, and governments of other countries that will be using the data for research purposes. Potential users ('Licensees') to this Database must read this Usage Agreement and complete and submit the Application for Access to The Dorenfest Institute for H.I.T. Research and Education Database included within this Usage Agreement.

The Database will be available to the Licensee via a secured Web site.

2. Term of License

Authorized Licensees will receive access to the Database for a period of six (6) months from the time the application is approved.

3. Nature of License

- The Licensee acknowledges and agrees that: (i) the Licensed Data is proprietary to and the confidential property of the Licensor and constitutes valuable information in which the Licensor holds all trade secret rights and copyrights; (ii) the Licensee acquires no right(s) in the Licensed Data except to use the Licensed Data solely within the Licensee's own organization or agency and for the Licensee's own purposes during the License Term in accordance with this Agreement; and (iii) the Licensee and its affiliates will not challenge the rights claimed by the Licensor in the Database and the Licensed Data. The Licensee agrees to treat the Licensed Data in the same manner as the Licensee's most confidential information, but in any event not less than a reasonable degree of care.
- The Licensee will take appropriate measures, by instruction, agreement, or otherwise, to ensure compliance with this Agreement during his or her relationship with the Licensee and thereafter pursuant to this Agreement. Unless the Licensee has obtained the express prior written authorization of the Licensor, the Licensee shall not use all or any part(s) of the Licensed Data for numerical or text quotation(s) for advertising or public relations. The Licensee shall not copy or reproduce in any form any or all of the Licensed Data unless the use of that data is related to the research project described in the Licensee's Usage Agreement and Application for Access to The Dorenfest Institute for H.I.T. Research and Education Database. However, under no circumstances can the Licensee reproduce the Database in its entirety.
- The Licensee agrees to cite the source of the data used from The Dorenfest Institute for H.I.T. Research and Education Database. The following language must appear at the bottom of each page in an article or research paper in which the data is cited:

Data Source: The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, Chicago, Illinois, 2010.

- The Licensee agrees to keep the unique password provided to the Database private and not share it with individuals not covered in the Application.
- The Licensee agrees to submit the written results of the research project (e.g., white paper, research report, thesis, article) to The Dorenfest Institute within 30 (thirty) days after the conclusion of the research project. The Licensor will have the right to post the report, article, or thesis on the Dorenfest Web site, as part of the Dorenfest database, unless the Licensee has submitted the document for publication in a professional journal, magazine or book.
- The Licensee should indicate whether the report, thesis, article, etc. will be submitted for publication.
- Notwithstanding the above, the Licensee shall have no obligations with respect to any information in or about the Licensed Data demonstrated to have already been known to the Licensee before receipt of the Licensed Data, or otherwise is or becomes part of the public domain without violation of this Agreement.

4. Warranty

The Licensee acknowledges that the data in the Database are collected by or on behalf of the Licensor and, while the Licensor reasonably believes such data to be accurate, the Licensor makes and Licensee receives no warranty, express or implied, and all warranties of merchantability and fitness for a particular purpose are expressly excluded. The Licensor shall have no liability with respect to any or all of its duties and obligations under this agreement for consequential, exemplary, special, or incidental damages, even if the Licensor has been advised of the possibility of such damages. In no event shall the Licensor's liability for damages, regardless of the form of action, exceed the amount paid by the licensee for the relevant licensed data.

5. Termination

Whenever the Licensor has knowledge or reason to believe that the Licensee has failed to observe any of the terms and conditions of this Agreement, the Licensor shall notify the Licensee in writing of the suspected breach. If, within 30 days of such notice, the Licensee fails to prove to the Licensor's reasonable satisfaction that the Licensee has not breached this Agreement, the Licensor may terminate the License and this Agreement.

6. Other

- The Licensee may not assign or sub-license to any person or entity its rights, duties, or obligations under this Agreement, to any person or entity, in whole or in part. This Agreement is binding upon the Parties and their respective heirs, assigns, and successors in interest.
- This Agreement and performance hereunder shall be governed by the laws of the State of Illinois without reference to conflicts of laws provisions.
- Notwithstanding anything to the contrary in this Agreement, the Licensee acknowledges and agrees that the Licensor in its sole discretion may change any or all of the format and content of the database at any time.

Appendix B: Registration for the Dorenfest Institute for HIT Research and Education Database

Solomon:

Thank you for your interest in registering for the Dorenfest Institute. As a reminder, the information stored within the database is being provided at no charge to eligible applicants who have agreed to all specified terms within the Usage Agreement and Application for the Dorenfest Institute for H.I.T. Research and Education Database.
Your application has been accepted and you may log-in by visiting the following link: http://apps.himss.org/DorenfestInstitute/login.aspx.
Username: skoppoe
Password: HIMSS15
Your access privileges will be active for six months through 7/6/15.
Per the agreement, please email or mail your completed project to us within 30 days of completion (see below for contact information). The information in the database is to only be used for the stated purpose of the project listed in the application and is not to be disseminated for use to any other parties.
Please let me know if you have any questions.
Jennifer

Jennifer Horowitz
Senior Director, Research
HIMSS Analytics
Know. Understand. Prepare. Change.

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HIMSS Asia Pacific | HIMSS Europe | HIMSS Latin America | HIMSS Middle East | HIMSS UK

From: Solomon Koppoe [mailto:redacted]
Sent: Sunday, January 18, 2015 1:41 AM
To: Horowitz, Jennifer
Subject: Re: Dorenfest Institute Access

Hello Jennifer,

Thanks very much for approving my application to gain access to the Dorenfest Institute of H.I.T. Research and Education Database. I do not need to access the database till after June or July of 2015 since I will not enter into my dissertation phase till then. Consequently, I would like to ask that the my 6-month access duration be delayed till I formally start my dissertation.

Thanks again for all your help.

Regards,
Solomon

Appendix C: Usage Agreement for the AHA Data View

Solomon,

If you would like to limit the data by region, type of hospital, etc. then we can develop a custom set of data for you.

Here is a link to the 2015 IT Survey, if you want to highlight the information that you will need then I can supply you with some cost estimates for the data.

https://www.ahadataviewer.com/Global/survey%20instruments/2015AHAITq.pdf

Also, I am not sure that we discussed that the 2016 IT data set will be out in early June and then 2017 will be out a year from now.

Let me know what else you need at this time.

redacted

NOTE: My email domain has changed due to a rebranding initiative here at AHA/Health Forum! Thanks for updating my email address to redacted@aha.org

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Appendix D: Results for the Entire t-Test for Region, Ownership Status, Number of Staffed Beds (Size), and Organizational Control

The following tables represent the entire SPSS output for the t-test for Region, Ownership Status, Number of Staffed Beds (Size) and Organizational Control.

Table D24

Independent Samples Test: Region

		Laverne's Test for Equality of Variances		t-test for Equality of Means					95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes (CDSS)	Equal variances assumed	.176	.675	-2.735	167	.007	-66.115	24.170	-113.832	-18.397
	Equal variances not assumed			-2.733	165.518	.007	-66.115	24.195	-113.885	-18.344
EHR Software Application Attributes (Components)	Equal variances assumed	.141	.707	-2.447	167	.015	-65.892	26.933	-119.065	-12.720
	Equal variances not assumed			-2.446	166.465	.016	-65.892	26.943	-119.086	-12.699
Successful Implementation of MU	Equal variances assumed	.128	.721	-2.423	167	.016	-78.197	32.268	-141.902	-14.492
	Equal variances not assumed			-2.423	166.503	.016	-78.197	32.279	-141.924	-14.469

Table D25

Independent Samples Test: Ownership Status

		Laverne's Test for Equality of Variances		t-test for Equality of Means					95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes	Equal variances assumed	.011	.918	1.464	167	.145	61.368	41.918	-21.390	144.125

(CDSS)	Equal variances not assumed			1.428	18.077	.170	61.368	42.987	-28.918	151.653
EHR Software Application Attributes (Components)	Equal variances assumed	.021	.886	1.323	167	.188	61.591	46.564	-30.338	153.520
	Equal variances not assumed			1.317	18.243	.204	61.591	46.779	-36.595	159.776
Successful Implementation of MU	Equal variances assumed	.029	.864	1.336	167	.183	74.500	55.763	-35.592	184.591
	Equal variances not assumed			1.328	18.234	.200	74.500	56.084	-43.220	192.219

Table D26

Independent Samples Test: Number of Staffed Beds (Size)

				t-test for Equality of Means						
		Laverne's Test for Equality of Variances							95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes (CDSS)	Equal variances assumed	.506	.478	-1.878	167	.062	-49.722	26.482	-102.004	2.560
	Equal variances not assumed			-1.910	102.034	.059	-49.722	26.027	-101.346	1.901
EHR Software Application Attributes (Components)	Equal variances assumed	.002	.967	-2.296	167	.023	-67.111	29.233	-124.825	-9.397
	Equal variances not assumed			-2.319	100.228	.022	-67.111	28.945	-124.536	-9.686
Successful Implementation of MU	Equal variances assumed	.014	.907	-2.261	167	.025	-79.207	35.028	-148.362	-10.052
	Equal variances not assumed			-2.285	100.409	.024	-79.207	34.657	-147.963	-10.452

Table D27A

Independent Samples Test: Organizational Control

				t-test for Equality of Means					
	Laverne's Test for Equality of Variances							95% CI of the Difference	
Independent	F	Sig.	t	*df*	Sig.	Mean	Std. Error	Lower	Upper

Samples Test - Region						(2 Tailed)	Difference	Difference		
EHR Software Application Attributes (CDSS)	Equal variances assumed	1.226	.270	2.139	167	.034	75.999	35.536	5.841	146.156
	Equal variances not assumed			1.988	27.968	.057	75.999	38.238	-2.332	154.329
EHR Software Application Attributes (Components)	Equal variances assumed	.570	.451	1.991	167	.048	78.654	39.498	.674	156.635
	Equal variances not assumed			1.921	28.639	.065	78.654	40.953	-5.151	162.459
Successful Implementation of MU	Equal variances assumed	.655	.419	1.998	167	.047	94.500	47.303	1.111	187.890
	Equal variances not assumed			1.921	28.585	.065	94.500	49.184	-6.156	195.157

Appendix E: Results for the Entire Test of Normality

The following tables represent the entire SPSS output for the Test of Normality for t-test for EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems) and Successful Implementation of MU. Table 27 represent all the details for all the dependent variables for this study.

Table E28

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
EHR Software Application Attributes (CDSS Components)	169	100.0%	0	0.0%	169	100.0%
EHR Software Application Attributes (Major Systems)	169	100.0%	0	0.0%	169	100.0%
Successful Implementation of MU	169	100.0%	0	0.0%	169	100.0%

Descriptives

			Statistic	Std. Error
EHR Software Application Attributes (CDSS Components) DV1	Mean		318.69	12.314
	95% Confidence Interval for Mean	Lower Bound	294.38	
		Upper Bound	343.00	
	5% Trimmed Mean		320.35	
	Median		336.00	
	Variance		25625.286	
	Std. Deviation		160.079	
	Minimum		24	
	Maximum		567	
	Range		543	
	Interquartile Range		252	
	Skewness		.054	.187
	Kurtosis		-1.130	.371
EHR Software Application Attributes (Major Systems) DV2	Mean		291.62	13.663
	95% Confidence Interval for Mean	Lower Bound	264.64	
		Upper Bound	318.59	
	5% Trimmed Mean		290.96	
	Median		280.00	
	Variance		31546.488	
	Std. Deviation		177.613	
	Minimum		24	

	Maximum		560	
	Range		536	
	Interquartile Range		350	
	Skewness		.219	.187
	Kurtosis		-1.432	.371
Successful Implementation of MU DV3	Mean		349.49	16.364
	95% Confidence Interval for Mean	Lower Bound	317.19	
		Upper Bound	381.80	
	5% Trimmed Mean	348.56	348.56	
	Median	336.00	336.00	
	Variance	45252.275	45252.275	
	Std. Deviation	212.726	212.726	
	Minimum	30	30	
	Maximum	672	672	
	Range	642	642	
	Interquartile Range	420	420	
	Skewness	.228	.228	.187
	Kurtosis	-1.428	-1.428	.371

Appendix F: Histograms and Scatter Plots Showing Dependent Variables on a Continuous Scale

Figures 1-15 show the EHR Software Application Attributes (CDSS Components) DV1

EHR Software Application Attributes (CDSS Components) DV1 – Figures 1 – 3

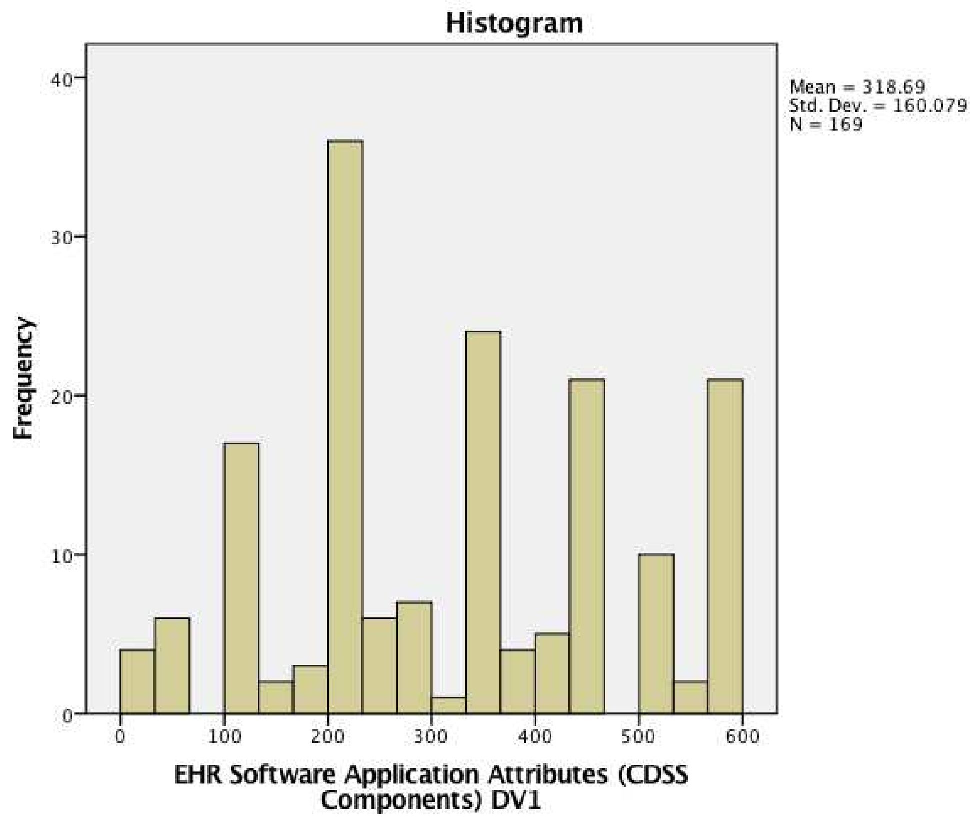

*Figure F1***.** EHR Software Application Attributes (CDSS Components) DV1

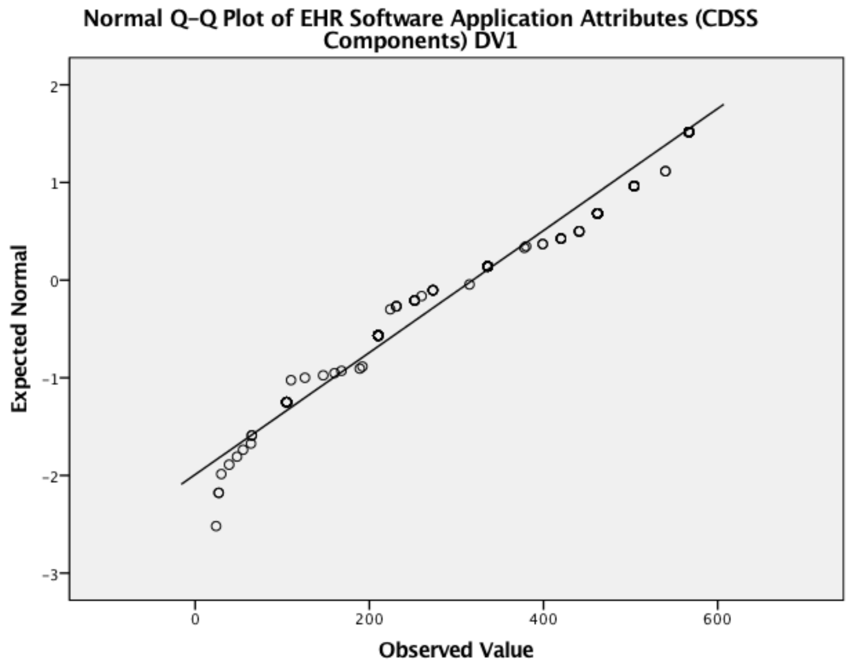

*Figure F2***.** Normal Q-Q Plot of EHR Software Application Attributes (CDSS Components) DV1

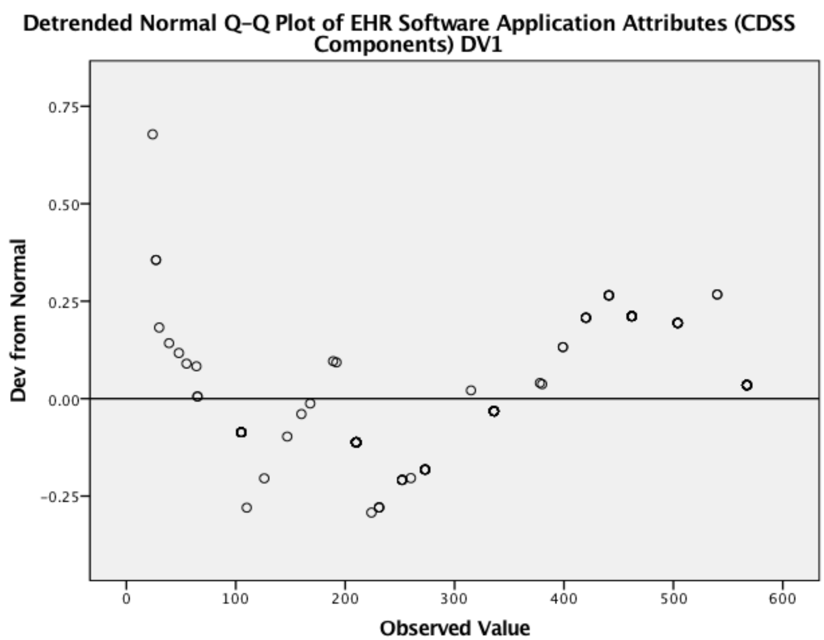

*Figure F3***.** Detrended Normal Q-Q Plot of EHR Application (CDSS Components) DV1

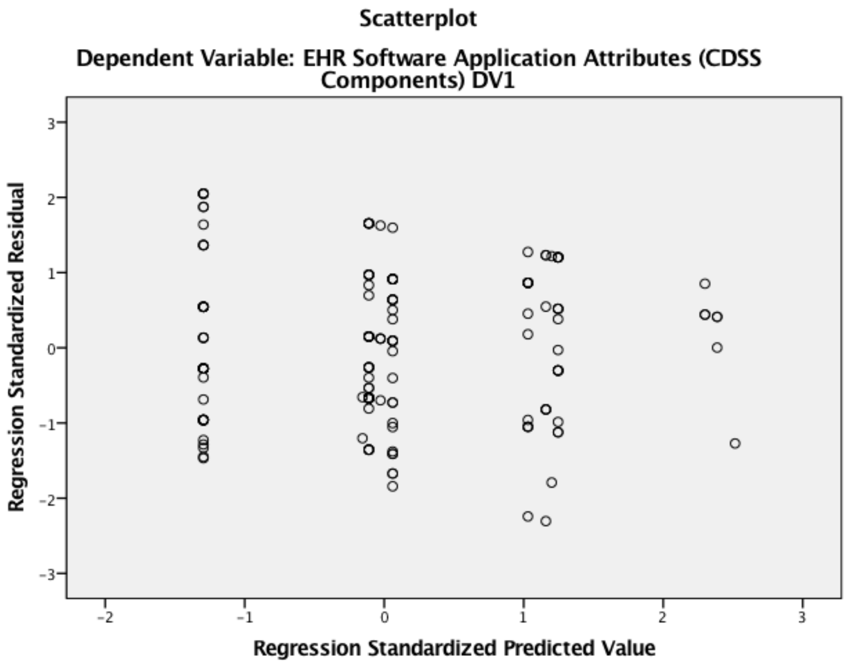

Figure F4. Dependent Variable: HER Software Application Attributes (CDSS Components) DV1

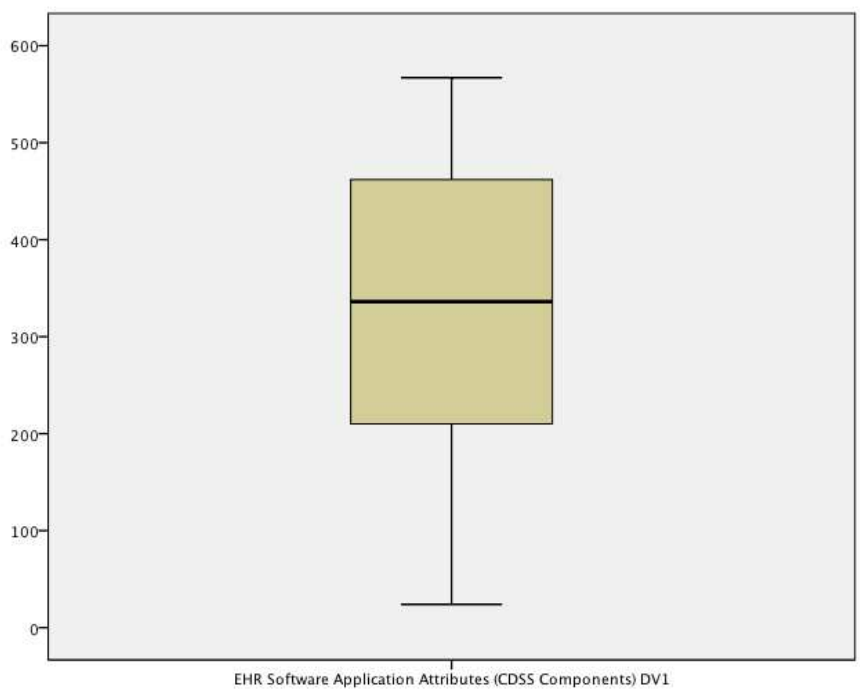

Figure F5. EHR Software Application Attributes (Major Systems) DV2

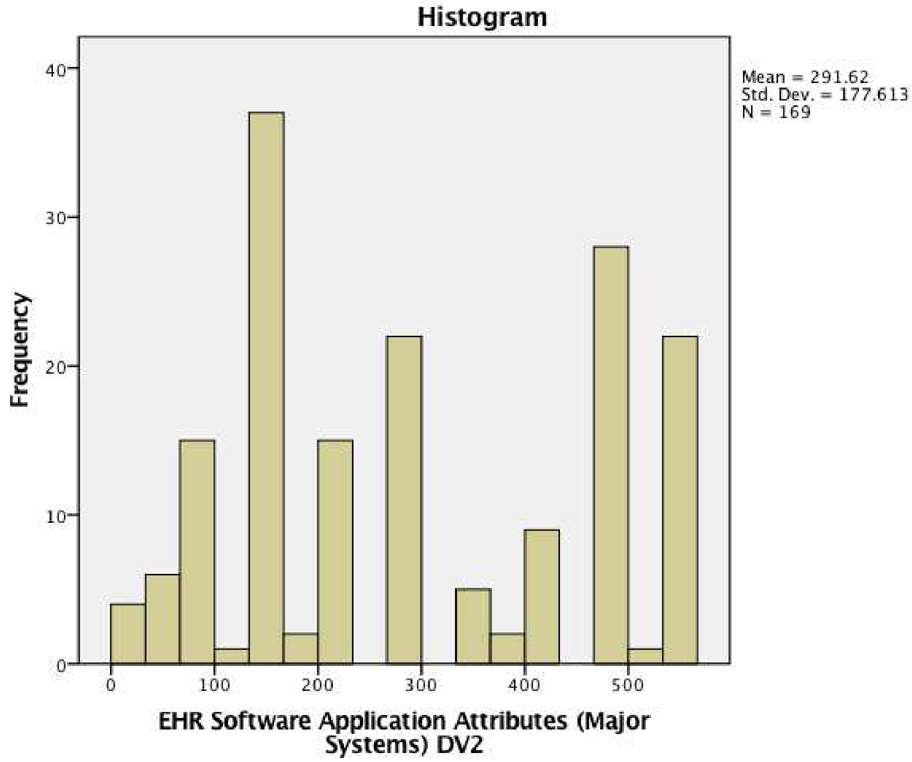

Figure F6. EHR Software Application Attributes (Major Systems) DV2

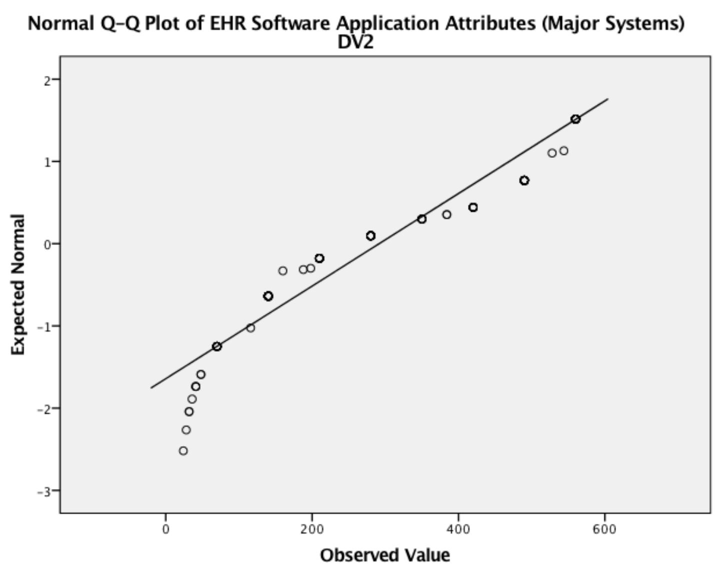

Figure 7. Normal Q-Q Plot Software Application Attributes (Major Systems) DV2

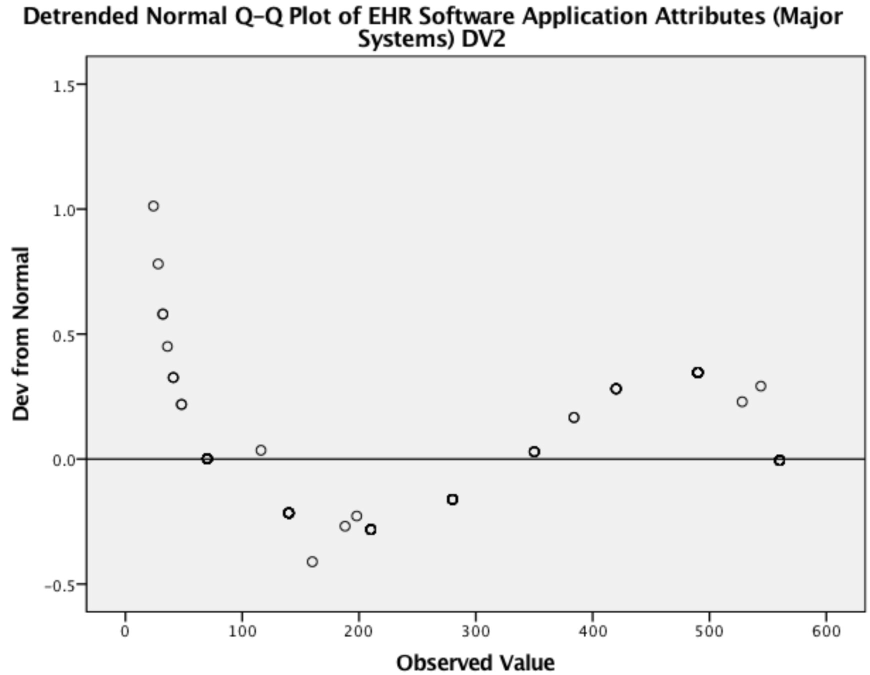

Figure 8. Detrended Normal Q-Q Plot of EHR Software Application Attributes (Major Systems) DV2

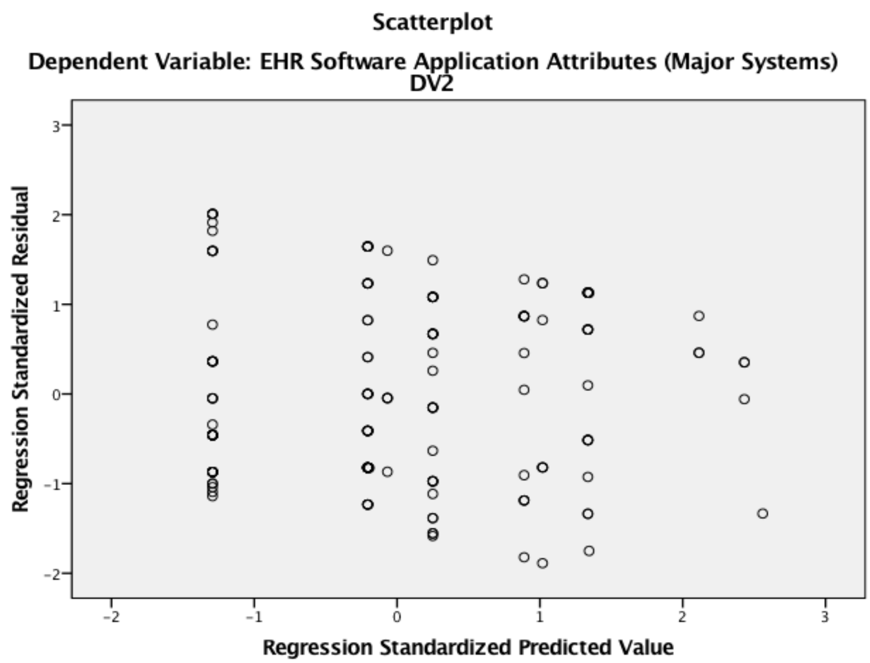

*Figure 9.*Dependent Variable: EHR Software Application Attributes (Major Systems) DV2

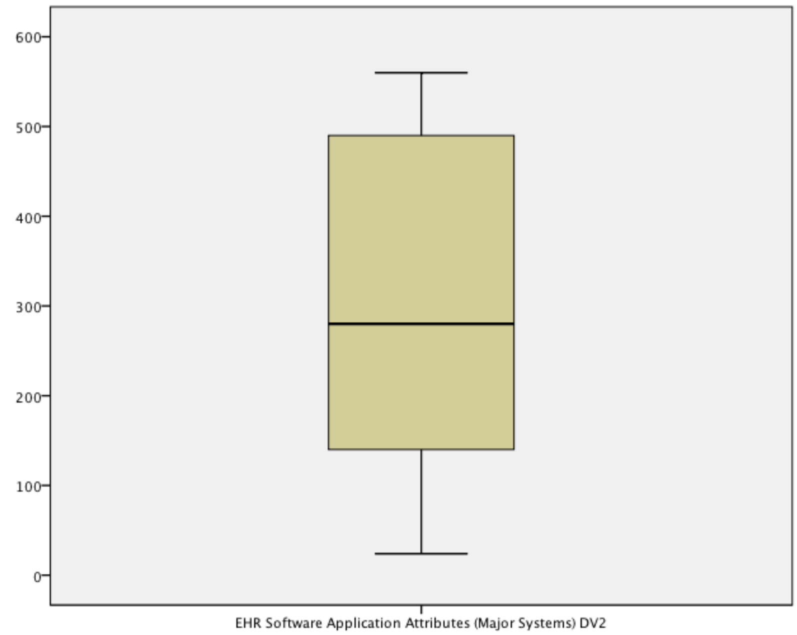

Figure 10. Dependent Variable: EHR Software Application Attributes (Major Systems) DV2

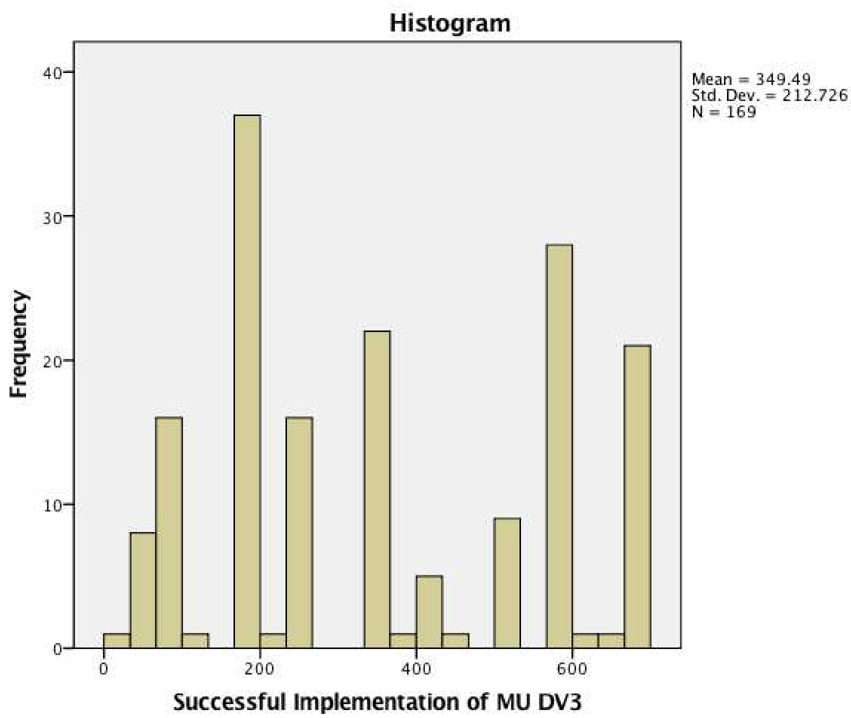

Figure 11. Successful Implementation of MU DV3

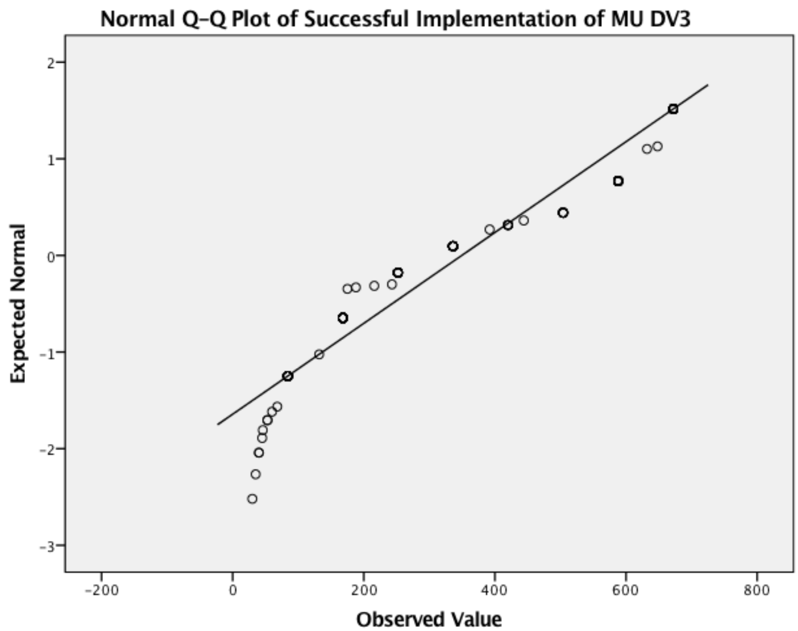

Figure 12. Normal Q-Q Plot of Successful Implementation of MU DV3

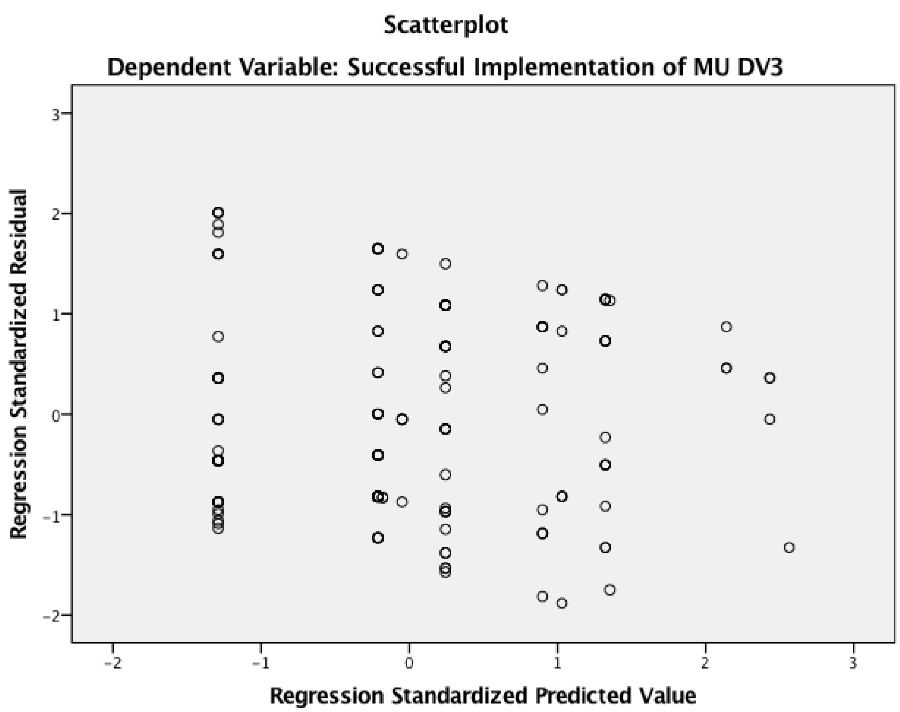

Figure 13. Dependent Variable: Successful Implementation of MU DV3

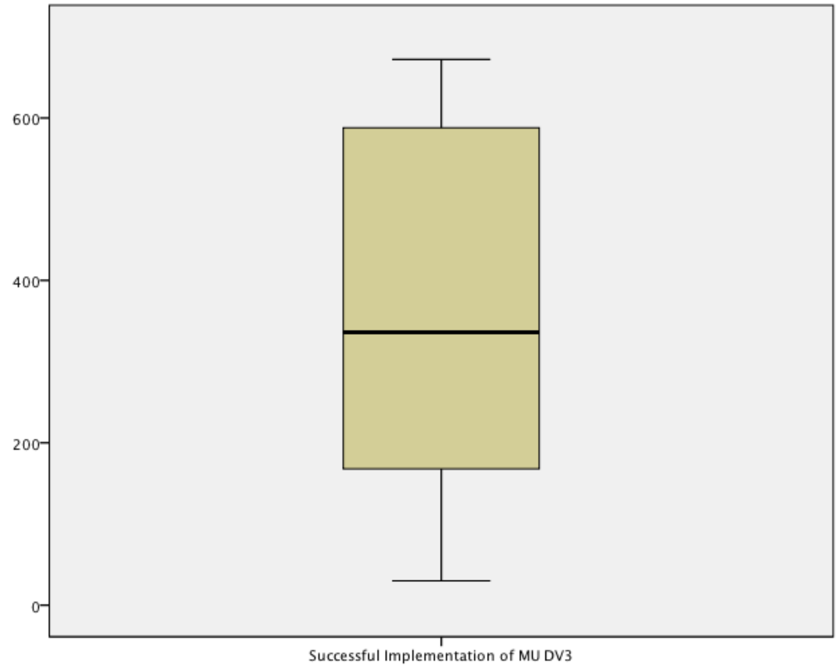

Figure 14. Dependent Variable: Successful Implementation of MU DV3

Appendix G: Results of the Pearson's Correlation Coefficient Test

Table 29 demonstrate the results from the Test for Correlation for Region, Ownership Status, Number Staffed Beds (Size) and Organizational Control with the complete SPSS output for the respective criterion variable in their entirety. Summary results have been provided in the Results of this study.

Table G29

Pearson's Correlation Coefficient Test: Region

			Region	Ownership Status	Staffed Beds (Size)	Org. Control	EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
Region	Pearson Correlation		1	-.116	-.140	-.252**	.207**	.186*	.184*
	Sig. (2-tailed)			.135	.069	.001	.007	.015	.016
	Sum of Squares and Cross-products		42.237	-2.858	-5.462	-7.296	2792.462	2783.077	3302.763
	Covariance		.251	-.017	-.033	-.043	16.622	16.566	19.659
	N		169	169	169	169	169	169	169
	Bootstrap Bias		0	.002	.002	.003	.000	.000	.000
	Std. Error		0	.073	.077	.065	.078	.078	.078
	95% Confidence Interval	Lower	1	-.253	-.285	-.369	.057	.032	.028
		Upper	1	.038	.017	-.106	.356	.333	.334

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

			Region	Ownership Status	Staffed Beds (Size)	Org. Control	EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
Ownership Status	Pearson Correlation		-.116	1	.172*	.048	-.113	-.102	-.103
	Sig. (2-tailed)		.135		.026	.531	.145	.188	.183
	Sum of Squares and Cross-products		-2.858	14.485	3.923	.822	-888.923	-892.154	-1079.142
	Covariance		-.017	.086	.023	.005	-5.291	-5.310	-6.423
	N		169	169	169	169	169	169	169
	Bootstrap Bias		.002	0	-.001	.001	-.001	.000	.000
	Std. Error		.073	0	.048	.084	.077	.075	.075
	95% Confidence Interval	Lower	-.253	1	.070	-.100	-.254	-.245	-.246
		Upper	.038	1	.257	.222	.047	.049	.049

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Pearson's Correlation Coefficient Test: Staffed Beds (Size)

			Region	Ownership Status	Staffed Beds (Size)	Org. Control	EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
Staffed Beds (Size) IV3	Pearson Correlation		-.140	.172*	1	.078	.144	.175*	.172*
	Sig. (2-tailed)		.069	.026		.316	.062	.023	.025
	Sum of Squares and Cross-products		-5.462	3.923	36.000	2.077	1790.000	2416.000	2851.462
	Covariance		-.033	.023	.214	.012	10.655	14.381	16.973
	N		169	169	169	169	169	169	169
	Bootstrap Bias		.002	-.001	0	.001	.001	.000	.000
	Std. Error		.077	.048	0	.071	.076	.077	.077
	95% Confidence Interval	Lower	-.285	.070	1	-.068	-.003	.023	.024
		Upper	.017	.257	1	.211	.294	.328	.327

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Pearson's Correlation Coefficient Test: Organizational Control

			Region	Ownership Status	Staffed Beds (Size)	Org. Control	EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
Org. Control	Pearson Correlation		-.252**	.048	.078	1	-.163*	-.152*	-.153*
	Sig. (2-tailed)		.001	.531	.316		.034	.048	.047
	Sum of Squares and Cross-products		-7.296	.822	2.077	19.870	-1510.077	-1562.846	-1877.704
	Covariance		-.043	.005	.012	.118	-8.989	-9.303	-11.177
	N		169	169	169	169	169	169	169
	Bootstrap Bias		.003	.001	.001	0	.003	.003	.003
	Std. Error		.065	.084	.071	0	.083	.080	.080
	95% Confidence Interval	Lower	-.369	-.100	-.068	1	-.316	-.299	-.301
		Upper	-.106	.222	.211	1	.004	.013	.014

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed)
.

Appendix H: Results for Entire t-Tests for EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems), and Successful Implementation of MU

The following represent the entire SPSS output for the t-tests for EHR Software Application Attributes (CDSS Components), EHR Software Application Attributes (Major Systems), Successful Implementation of MU. These tests represent only the statistically significant results for the t-tests. Tables 29 to 43 show the group statistics and the t-test for Equality of Means.

Table H30

Group Statistics – Region and EHR Software Application Attributes (CDSS Components)

	Region	N	M	SD	SEM
EHR Software Application Attributes (CDSS Components)	Region 1 (ME, NH, MA, CT, VT, RI, NY, NJ, PA, DE)	83	285.05	161.729	17.752
	Region 2 (MD, WV, DC, VA, NC, KY	86	351.16	152.455	16.440

Table H31

Group Statistics – Region and EHR Software Application Attributes (Major Systems)

	Region	N	M	SD	SEM
EHR Software Application Attributes (Major Systems)	Region 1 (ME, NH, MA, CT, VT, RI, NY, NJ, PA, DE)	83	258.08	176.896	19.417
	Region 2 (MD, WV, DC, VA, NC, KY	86	323.98	173.221	18.679

Table H32

Group Statistics – Region and Successful Implementation of MU

	Region	N	M	SD	SEM
Successful Implementation of MU	Region 1 (ME, NH, MA, CT, VT, RI, NY, NJ, PA, DE)	83	309.70	211.717	23.239
	Region 2 (MD, WV, DC, VA, NC, KY	86	387.90	207.748	22.402

Table H33

Independent Samples Test: Region

	t-test for Equality of Means								
	Laverne's Test							95% CI of the Difference	
Independent Samples Test - Region	F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper

EHR Software Application Attributes (CDSS)	Equal variances assumed	.176	.675	-2.735	167	.007	-66.115	24.170	-113.832	-18.397
	Equal variances not assumed			-2.733	165.518	.007	-66.115	24.195	-113.885	-18.344
EHR Software Application Attributes (Major Systems)	Equal variances assumed	.141	.707	-2.447	167	.015	-65.892	26.933	-119.065	-12.720
	Equal variances not assumed			-2.446	166.465	.016	-65.892	26.943	-119.086	-12.699
Successful Implementation of MU	Equal variances assumed	.128	.721	-2.423	167	.016	-78.197	32.268	-141.902	-14.492
	Equal variances not assumed			-2.423	166.503	.016	-78.197	32.279	-141.924	-14.469

Table H34

Group Statistics – Ownership Status and EHR Software Application Attributes (CDSS Components)

	Ownership Status	N	M	SD	SEM
EHR Software Application Attributes (CDSS Components)	Managed	16	374.25	164.074	41.018
	Owned	153	312.88	159.082	12.861

Table H35

Group Statistics – Ownership Status and EHR Software Application Attributes (Major Systems)

	Ownership Status	N	M	SD	SEM
EHR Software Application Attributes (Major Systems)	Managed	83	309.70	211.717	23.239
	Owned	86	387.90	207.748	22.402

Table H36

Group Statistics – Ownership Status and Successful Implementation of MU

	Ownership Status	N	M	SD	SEM
Successful Implementation of MU	Managed	16	416.94	213.593	53.398
	Owned	153	342.44	212.096	17.147

Table H37

Independent Samples Test: Ownership Status

				t-test for Equality of Means						
		Laverne's Test		`					95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes (CDSS)	Equal variances assumed	.011	.918	1.464	167	.145	61.368	41.918	-21.390	144.125
	Equal variances			1.428	18.077	.170	61.368	42.987	-28.918	151.653

		F	Sig.	t	df	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
	not assumed									
EHR Software Application Attributes (Components)	Equal variances assumed	.021	.886	1.323	167	.188	61.591	46.564	-30.338	153.520
	Equal variances not assumed			1.317	18.243	.204	61.591	46.779	-36.595	159.776
Successful Implementation of MU	Equal variances assumed	.029	.864	1.336	167	.183	74.500	55.763	-35.592	184.591
	Equal variances not assumed			1.328	18.234	.200	74.500	56.084	-43.220	192.219

Table H38

Group Statistics – Number of Staffed Beds (Size) and EHR Software Application Attributes (CDSS Components)

	Number of Staffed Beds (Size)	N	M	SD	SEM
EHR Software Application Attributes (CDSS Components)	Bed Size ≤ 250	117	303.39	161.010	14.885
	Bed Size >250	52	353.12	153.956	21.350

Table H39

Group Statistics – Number of Staffed Beds (Size) and EHR Software Application Attributes (Major Systems)

	Number of Staffed Beds (Size)	N	M	SD	SEM
EHR Software Application Attributes (Major Systems)	Bed Size ≤ 250	117	270.97	176.748	16.340
	Bed Size >250	52	338.08	172.288	23.892

Table H40

Group Statistics – Number of Staffed Beds (Size)and Successful Implementation of MU

	Number of Staffed Beds (Size)	N	M	SD	SEM
Successful Implementation of MU	Bed Size ≤ 250	117	325.12	211.908	19.591
	Bed Size >250	52	404.33	206.157	28.589

Table H41

Independent Samples Test: Number of Staffed Beds (Size)

		Laverne's Test		t-test for Equality of Means					95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes (CDSS)	Equal variances assumed	.506	.478	-1.878	167	.062	-49.722	26.482	-102.004	2.560
	Equal variances not assumed			-1.910	102.034	.059	-49.722	26.027	-101.346	1.901
EHR Software Application Attributes (Components)	Equal variances assumed	.002	.967	-2.296	167	.023	-67.111	29.233	-124.825	-9.397
	Equal variances not			-2.319	100.228	.022	-67.111	28.945	-124.536	-9.686

		F	Sig.	t	df	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
	assumed									
Successful Implementation of MU	Equal variances assumed	.014	.907	-2.261	167	.025	-79.207	35.028	-148.362	-10.052
	Equal variances not assumed			-2.285	100.409	.024	-79.207	34.657	-147.963	-10.452

Table H42

Group Statistics – Organizational Control and EHR Software Application Attributes (CDSS Components)

	Organizational Control	N	M	SD	SEM
EHR Software Application Attributes (CDSS Components)	Government, non-federal	23	384.35	172.593	35.988
	Non-Government, non-for-profit (NFP)	146	308.35	156.137	12.922

Table H43

Group Statistics – Organizational Control and EHR Software Application Attributes (Major Systems)

	Organizational Control	N	M	SD	SEM
EHR Software Application Attributes (Major Systems)	Government, non-federal	23	359.57	183.732	38.311
	Non-Government, non-for-profit (NFP)	146	280.91	174.874	14.473

Table H44

Group Statistics – Organizational Control and Successful Implementation of MU

	Organizational Control	N	M	SD	SEM
Successful Implementation of MU	Government, non-federal	23	431.13	220.765	46.033
	Non-Government, non-for-profit (NFP)	146	336.63	209.313	17.323

Table H45

Independent Samples Test: Organizational Control

		t-test for Equality of Means								
		Laverne's Test							95% CI of the Difference	
Independent Samples Test - Region		F	Sig.	t	*df*	Sig. (2 Tailed)	Mean Difference	Std. Error Difference	Lower	Upper
EHR Software Application Attributes (CDSS)	Equal variances assumed	1.226	.270	2.139	167	.034	75.999	35.536	5.841	146.156
	Equal variances not assumed			1.988	27.968	.057	75.999	38.238	-2.332	154.329
EHR Software Application Attributes (Components)	Equal variances assumed	.570	.451	1.991	167	.048	78.654	39.498	.674	156.635
	Equal variances not assumed			1.921	28.639	.065	78.654	40.953	-5.151	162.459
Successful Implementation of MU	Equal variances assumed	.655	.419	1.998	167	.047	94.500	47.303	1.111	187.890

Equal variances not assumed	1.921	28.585	.065	94.500	49.184	-6.156	195.157

Appendix I: Linear Regression Testing Results for Dependent Variables

The following results in Tables 45 to 47 are from the complete linear regression analysis for the predictors and EHR Software Application Attributes (CDSS Components).

Table I46

Coefficients for Predictors of EHR Software Application Attributes (CDSS Components)

	b	*Standard Error (B)*	*B*	*t*	*Coefficients p*
Region	60.621	24.699	.190	2.454	.015
Ownership Status	-64.879	41.134	-.119	-1.577	.117
Number of Staffed Beds (Size)	69.353	26.196	.201	2.647	.009
Organizational Control	-58.303	35.629	-.125	-1.636	.104

Table I47

Coefficients for Predictors of EHR Software Application Attributes (Major Systems)

	b	*Standard Error (B)*	*B*	*t*	*Coefficients p*
Region	61.763	27.397	.174	2.254	.025
Ownership Status	-69.610	45.628	-.115	-1.526	.129
Number of Staffed Beds (Size)	87.659	29.058	.228	3.017	.003
Organizational Control	-62.257	39.521	-.121	-1.575	.117

Table I48

Coefficients for Predictors of Successful Implementation of MU

	b	*Standard Error (B)*	*B*	*t*	*Coefficients p*
Region	72.964	32.839	.172	2.222	.028
Ownership Status	-83.941	54.691	-.116	-1.535	.127
Number of Staffed Beds (Size)	103.756	34.829	.226	2.979	.003
Organizational Control	-75.080	47.371	-.121	-1.585	.115

Appendix J: Results of the Variance Inflection Factor – Test for Multicollinearity

The final assumption is for independent errors, which is when two observations are truly uncorrelated, on indicate no concerns for multicollinearity. The variance inflation factor (VIF) can be reviewed for multicollinearity. A VIF of less than 5, or a Tolerance level of less than 1 indicate no multicollinearity (Field 2013). Table 48 shows the results of the collinearity statistics for the predictor variables.

Table J49

VIF Values (Collinearity) and Tolerance Results for Research Question 1

Independent Variables	Tolerance	Average VIF
Region	.915	1.093
Ownership Status	.962	1.040
Number of Staffed Bed (Size)	.954	1.048
Organizational Control	.935	1.070

Appendix K: Independent Variables and Dependent Variables Code Book

The following is the revised coding of the independent variables and dependent variables. The coding submitted in the Dissertation Proposal document was based on the data dictionary provided by HIMSS. Table 49 and Table 50 show the revised coding for the independent variables and dependent variables which was based on the actual data downloaded from the HIMSS website.

Table K50

Independent Variables Codebook

Variable	Subcategory / Term	Code	Description
Hospital Attributes	Facility Type - Hospital		**Hospitals**
	Organizational Control	1 2	Government, non-federal Non-Government, non-for-profit
	Ownership Status	1 2	Managed Hospitals Owned Hospitals
	Number of Staffed Beds (Size)	1 2	Beds <= 250 Beds ≥ 250

Table K51

Dependent Variables Codebook

Variable	Subcategory / Term	Code	Description
EHR Software Application Attributes (Major Systems)	Cardiology Information System	1	
	Anesthesia Information Management System (AIMS)	1	
	Location / Region - 1	R1	Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Delaware, Pennsylvania
	Location / Region - 2	R2	Maryland, West Virginia, Virginia, District of Columbia, North Carolina, Kentucky

	Emergency Department Information System	
	(EDIS)	1
	Respiratory Care Information System	
	Document Management	1
	Electronic Forms Management	1
	Clinical Decision Support System (CDSS)	1
	Computerized Practitioner Order Entry	1
	(CPOE)	
	Laboratory Information System	1
		1
		1
	Utilization Review/Risk Management for	
	Outcomes and Quality Management System	1
	Specimen Collection Management System	
	Transfusion Management System	1
	Electronic Medication Administration Record	
	(EMAR)	1
	Medication Reconciliation Software	
	Pharmacy Management System	1
	Radiology Information System	
	Outcomes and Quality Management	1
	Abstracting	
	Anatomical Pathology	1
	Case Mix Management	1
	Chart Deficiency	1
	Telemedicine	1
		1
		0
		0
		0
		0
		0
EHR Software Application Attributes		
(CDSS Components)	Drug dosing interactions	1
	Drug interactions (drug/drug, drug/lab,	
	drug/food)	1
	Drug Content	1
	Nursing/Clinician Content	1
	Clinical guidelines and pathways for nurses	
	Clinical guidelines and pathways for	0
	physicians	
	Patient Content	0
	Physician Content	0
		0
Successful Implementation of		
Meaningful Use (MU)	Cardiology & PACS	
	Clinical Systems	1
	Document/Forms Management	1
	Electronic Medical Record	
	Laboratory Testing and Results	1
	Pharmacy	1
	Radiology & PACS	
	Nursing	1
	Telemedicine	1
		1

0
0

Codebook for Dependent & Independent Variables

Appendix L: Results for the Entire Test of Normality for Successful Implementation of MU

The following tables represent the entire SPSS output for the Test of Normality for t-test for Successful Implementation of MU. Table 51 and Table 52 represent all the details for all the dependent variables for this study.

Table L52

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Successful Implementation of MU	169	100.0%	0	0.0%	169	100.0%

				Statistic	Std. Error
Successful Implementation of MU DV	Mean			349.49	16.364
	95% Confidence Interval for Mean	Lower Bound		317.19	
		Upper Bound		381.80	
	5% Trimmed Mean		348.56	348.56	
	Median		336.00	336.00	
	Variance		45252.275	45252.275	
	Std. Deviation		212.726	212.726	
	Minimum		30	30	
	Maximum		672	672	
	Range		642	642	
	Interquartile Range		420	420	
	Skewness		.228	.228	.187
	Kurtosis		-1.428	-1.428	.371

Appendix M: Results of the Pearson's Correlation Coefficient Test

Tables 53 – 55 demonstrate the results from the Test for Correlation for EHR Software Application Attributes (Major Systems) and EHR Software Application Attributes (CDSS Components) with the complete SPSS output for the respective criterion variable in their entirety. Summary results have been provided in the Results of this study.

Table M53

Pearson's Correlation Coefficient Test: EHR Software Application Attributes (CDSS Components)

			EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
EHR Software Application Attributes (CDSS Components)	Pearson Correlation		1	.985**	.985**
	Sig. (2-tailed)			.000	.000
	Sum of Squares and Cross-products		4305048.000	4706846.000	5635890.538
	Covariance		25625.286	28016.940	33546.967
	N		169	169	169
	Bootstrap Bias		0	.000	.000
	Std. Error		0	.002	.002
	95% Confidence Interval	Lower	.	.982	.981
		Upper	.	.989	.988

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table M54

Pearson's Correlation Coefficient Test: EHR Software Application Attributes (Major Systems)

			EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
EHR Software Application Attributes (Major Systems)	Pearson Correlation		.985**	1	1.000**
	Sig. (2-tailed)		.000		.000
	Sum of Squares and Cross-products		4706846.000	5299810.000	6345034.923
	Covariance		28016.940	31546.488	37768.065
	N		169	169	169
	Bootstrap Bias		.000	0	.000
	Std. Error		.002	0	.000
	95% Confidence Interval	Lower	.982	.	.999
		Upper	.989	.	1.000

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table M55

Pearson's Correlation Coefficient Test: Successful Implementation of MU

		EHR Software Application Attributes (CDSS Components)	EHR Software Application Attributes (Major Systems)	Successful Implementation of MU
Successful Implementation of MU	Pearson Correlation	.985**	1.000**	1
	Sig. (2-tailed)	.000	.000	
	Sum of Squares and Cross-products	5635890.538	6345034.923	7602382.237
	Covariance	33546.967	37768.065	45252.275
	N	169	169	169
	Bootstrap Bias	.000	.000	0
	Std. Error	.002	.000	0

Appendix N: Linear Regression Testing Results for Dependent Variables for RQ 2

The following results in Tables 56 are from the complete linear regression analysis for the predictors and Successful Implementation of MU.

Table N56

Coefficients for Predictors of Successful Implementation of MU

	b	*Standard Error (B)*	*B*	*t*	*Coefficients p*
EHR Software Application Attributes (CDSS Components)	.006	1.349	.005	.360	.719
EHR Software Application Attributes (Major Systems)	1.192	.015	.995	77.843	.001

Appendix O: Results of the Variance Inflection Factor – Test for Multicollinearity for RQ 2

The final assumption is for independent errors, which is when two observations are truly uncorrelated, on indicate no concerns for multicollinearity. The variance inflation factor (VIF) can be reviewed for multicollinearity. A VIF of less than 5, or a Tolerance level of less than 1 indicate no multicollinearity (Field 2013). Table 57 shows that the predictors do not indicate any concerns for multicollinearity and the relative importance of the independent variables in explaining the variation caused by the dependent variable can be determined.

Table O57

VIF Values (Collinearity) and Tolerance Results for Research Question 2

Independent Variables	Tolerance	Average VIF
EHR Software Application Attributes (CDSS Components)	1.000	1.000