2013

An Analysis of the External Environmental and Internal Organizational Factors Associated With Adoption of the Electronic Health Record

Clemens Kruse
Virginia Commonwealth University

An Analysis of the External Environmental and Internal Organizational Factors Associated With Adoption of the Electronic Health Record

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

by

Clemens Scott Kruse
M.H.A., Baylor University, 2005
M.S.I.T., University of Texas at San Antonio, 2005
M.B.A, University of Texas at San Antonio, 2004
B.S., United States Military Academy, 1991

Dissertation Director: Carolyn Watts, Ph.D.
Professor, Department of Health Administration

Virginia Commonwealth University
Richmond, Virginia

Acknowledgement

I need to thank several people. To my parents, Clem and Sandy; you taught me to have courage to stand up for what I believe. To my Scoutmaster, Mr. Fretz; you provided me with a sound ethical foundation and to stick with the hike. To my Squad Leader at West Point, Cadet Walls; you taught me to venerate the good examples and disdain the bad. To my Tactical Officer at West Point, Colonel (ret) Weart; you taught me compassion and the power of a second chance. To my mentor, Colonel (ret) Preczewski; you taught me to identify the reason for the solution. To my best friend, Colonel Chip Pierce; you taught me to laugh at life and myself. Finally, to my bride of 20 years; Susan; you encouraged me and supported me. I love you dearly.

Table of Contents

List of Tables

List of Figures

Abstract

AN ANALYSIS OF THE EXTERNAL ENVIRONMENTAL AND INTERNAL ORGANIZATIONAL FACTORS ASSOCIATED WITH ADOPTION OF THE ELECTRONIC HEALTH RECORD

By Clemens Scott Kruse, Ph.D.

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Virginia Commonwealth University

Virginia Commonwealth University, 2013

Dissertation Director: Carolyn Watts, Ph.D.
Professor, Department of Health Administration

Despite a Presidential Order in 2004 that launched national incentives for the use of health information technology, specifically the Electronic Health Record (EHR), adoption of the EHR has been slow. This study attempts to quantify factors associated with adoption of the EHR and Computerized Provider Order Entry (CPOE) by combining multiple organizational theories and empirical studies. The study is conducted in two phases. The primary phase of this study identifies and evaluates the effects of external environmental and internal organizational factors on healthcare organizations to adopt the EHR. From secondary data, twelve IVs (df=19) are chosen based on existing models and literature. Logistic regression is used to determine the association between

the environmental factors and EHR adoption. The secondary phase of this study examines the adoption of five variations of CPOE using the same IVs from phase one. This EHR component of CPOE is chosen due to its promotion as a solution to help cross the quality chasm (IOM, 2001). Secondary data are analyzed and logistic regression is used to quantify the association between the factors of EHR adoption and CPOE adoption. Eleven of the twelve IVs are significant between the two phases (p<.1). This study uses data from 2009 because the HITECH Act was passed that year and significant government incentives were offered for those health care organizations (HCOs) that meet the qualifications of meaningful use. This study serves as a baseline for future studies, extends the work of other empirical studies, and fills a gap in the literature concerning factors associated with the adoption of the EHR and specific dimensions of CPOE. The Kruse Theory developed is strongly based in literature and reflects complexity commensurate with the health care industry.

CHAPTER 1: Introduction

Terms and Acronyms in This Study

In an ongoing effort to assist the reader in navigating the logic of this dissertation through the litany of terms and acronyms, Appendix A lists the most common ones used. The taxonomy in the field of health information management is not always consistent, but the terms listed in the table will remain constant for this document.

Intent of the Study

The intent of this study is to evaluate external environmental and internal organizational factors associated with adoption of the Electronic Health Record (EHR). Health care organizations (HCOs) operate in the competitive market, but the added dimensions of third-party payers and the inherently personal nature of health care create layers of complexity that separates health care from other industries[1]. Because the HCO is a complex organization, a similarly complex theory is needed that combines multiple traditional theories such as resource dependence and diffusion of innovation. The theory developed by this study identifies and evaluates the internal and external factors that influence the decisions of healthcare organizations to adopt the EHR. Secondary data are drawn from two data sources: The American Hospital Association

[1] Porter (2005) summarizes the complexity of the healthcare industry: Its high cost and limited access, varying standards for and degrees of coverage, and the third-party payer system inherent to healthcare financing and delivery.

(AHA), and the Center for Medicare and Medicaid Services (CMS). Descriptive statistics and multivariate analysis assess the different characteristics between organizations that have implemented the EHR and those who have not (phase one), and of those HCOs that have adopted the EHR, and whether they have adopted any one of five varieties of Computerized Provider Order Entry (CPOE, phase two). In both phases, the DV is binary. The results contribute to an understanding of how organizations make the decision to adopt an EHR solution.

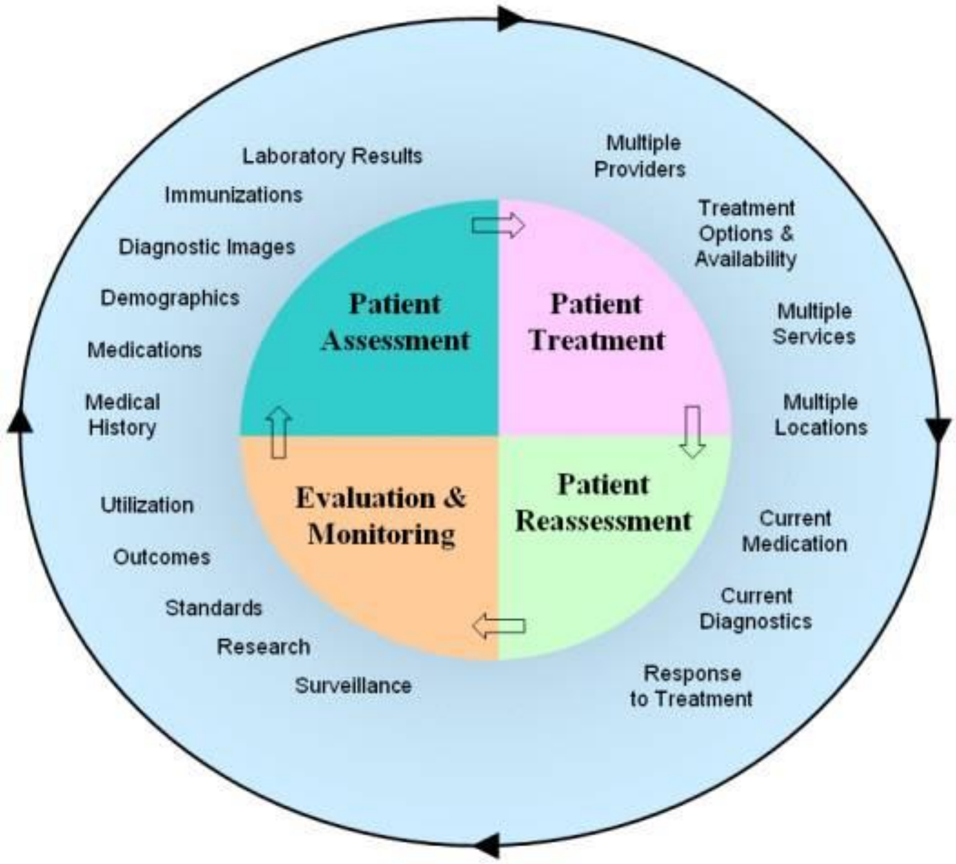
Adoption of an EHR solution is a significant decision that must be made by HCOs. The HCO is influenced by the CMS and other payers, physicians, patients, and competitors, and the influences are both internal and external (Rogers, 1995 & 2003; Pfeffer and Salancik, 1978; Wang, Wan, Burke, Bazzoli, & Lin, 2005). A complex organizational model is appropriate to evaluate this complex set of interdependencies.

The EHR – Scope and Significance

The EHR is widely misunderstood. In order to define its significance, however, it might help to identify what the EHR is not. The EHR is not a digitized version of a paper record. It is not one encounter. It is not a “flat” file, or one that cannot be searched, indexed, or integrated into a smart, relational system of records. The EHR is not limited to one facility, or organization, one multi-hospital system, or one state – it is fully interoperable and can be shared between disparate HCOs, enabling the provider to more efficiently provide the standard of care to the patient (Health Information Management Systems Society (HIMSS), 2013).

The EHR is far more than an electronic means of filing a patient's health record. The National Institute of Health recognizes the definition developed by the HIMSS. The EHR possesses a broader look on a patient other than the immediate appointment or incidence of care. The EHR attempts to serve as the continuity provider, looking over the entire collection of encounters (MITRE, 2006). The EHR builds on a master patient index containing patient demographics and a patient ID number. It then builds a large interactive, comprehensive interface between the provider and the health history, including diagnostic images, immunizations, lab results, treatment and progress notes, problem list, medications (and alerts), vital signs, and past medical history. Interoperability is enabled through the use of standardized medical language and international codes (e.g., International Classification of Diseases (ICD-10), Current Procedural Terminologies (CPT-10) codes, and Health Level 7 (HL7)). Clinical data are shared through health information exchanges located either regionally or statewide. The EHR automates and streamlines the clinician's and administrator's workflow, and as such, it can radically change the way an HCO operates. It has the ability to generate a complete record of a clinical patient encounter, as well as supporting other care-related activities directly or indirectly via interface – including evidence-based decision support, quality management, and outcomes reporting. In this way, the EHR can transcend both operational business processes and long-term organizational strategy. Figure 1 illustrates the breadth and scope of the EHR.

Figure 1. EHR Design, Breadth and Scope



Source: Manitoba eHealth, 2012.

Kruse Theory – Overview of the Conceptual Model

The Kruse theory is developed through a combination of established organizational theories such as Diffusion of Information (Rogers, 1995 & 2003) and Resource Dependence (Pfeffer & Salancik, 1978), and integrates empirical studies on influences (Wang et al., 2005) and organizational strategy (Bazzoli, Shortell, Dubbs, Chang, & Kravlovec, 1999). The Kruse theory posits a complex relationship between environmental influences, organizational strategy, and EHR adoption.

Elements of organizational strategy are not variables that can be easily changed (Bazzoli et al., 1999); therefore, elements typically ascribed to strategy, such as size, ownership, and fiscal stability, will be absorbed into the independent variables of influence. This research proposes a model whereby environmental factors are associated with an organization's decision to adopt the EHR.

Pfeffer and Salancik's (1978) work in Resource Dependence Theory explains environmental influences and the external interdependence of organizations. The authors' premise is that the external environment creates a social context and plays an important role in how organizational decisions are made. The interdependence of organizations widens the field of stakeholders, and this relationship effect should be defined.

Disparate stakeholders have different interests with reference to different components of the EHR. These interests may be different in the short run (SR) interests versus the long run (LR) interests. Short run interests are those that are immediate, such as current year expenditures. Long run interests are further out when all inputs are variable. The SR interests of cost can often compete with the LR potential of cost savings and greater safety. Both the SR and LR interests are affected by the external environment.

In a highly competitive environment, SR cost implications could often win over any long-term savings. The number of patients in a market is fixed in the SR, and a highly competitive market will affect each competitor's share of that market. The SR costs of EHR implementation might be insurmountable by an organization in this market because it could not afford to lose ground without significant capital reserves or the ability to borrow cheaply[2]. However, in a less competitive market, the LR interests of potential cost savings have a better chance of influencing the decision to implement an EHR because the costs incurred in the SR are justified by the long-term benefits[3].

External stakeholders that control resources important to the HCO can exert significant influence. For instance, an HCO that receives a significant amount of revenue from the CMS will be influenced more by incentives provided by the CMS than an organization that receives a significant cash flow from private third parties. The relative influence of various external stakeholders may be captured by an analysis of the structure of the market in which an HCO operates.

Stakeholders have varying interests with regard to the capabilities and effects of EHR components depending upon their relationship with the HCO. Private payers have both SR and LR interests in the EHR. In the SR, their focus is on minimizing expenditures. Because the HCO would pass on the implementation costs through higher contract costs, payers would not be equal in the SR. In addition, the disruption of EHR implementation could potentially affect care processes and therefore increase claims. Payers would be interested in the LR benefits of the EHR: Potential cost savings, better disease management, and increased safety. However, the SR interests of the private payers might overshadow the LR benefits of the EHR. Public payers enable care of the indigent and elderly. As part of the HHS, the CMS is highly

---

[2] Wu & Kuo (2012) discussed the necessity for the HCO to heavily invest in IT, and the detrimental short-term effect these large IT purchases have on the HCO.
[3] Henderson (2002) describes the economies of scale associated with larger versus smaller medical practices.

interested in disease management, public health, safety, and research, and it may value these LR capabilities of the EHR more than the SR costs. The CMS, as part of HHS, would also favor the EHR because it supports the Presidential directive to promote the establishment of the Nationwide Health Information Network (NHIN) that links electronic patient records through Health Information Exchanges.

Providers and patients value face time with each other. During EHR implementation, providers might spend less time in communication with patients. Providers must adapt their processes and clinic-to-administrative schedules. Any disruption or action that is perceived as deleterious to this relationship could result in a negative reaction to EHR implementation. As a result, physicians might oppose EHR adoption, or they might simply support the EHR solution with the shortest implementation time or least administrative burden. Patients might not like the reduced face time with the provider, but they might be attracted to EHR components such as e-prescribing, e-results, personal health records, and email access to the provider. These desirable features are available to the patient when the HCO chooses to adopt various portions of the CPOE component to the EHR.

CHAPTER 2: Background on The Electronic Health Record

This chapter focuses on the background of EHR adoption. I will operationally define the EHR and explain EHR adoption. This chapter is designed to help the reader start from the same point as the writer when considering this study and its associated development of a new organizational theory.

EHR Operationally Defined

The EHR is far more than an electronic means of filing a patient's health record. A scanned version of one medical encounter would not substantially differ from a paper version, but a digitized version of all of the encounters for a patient, across all specialties, organized in a searchable, relational database is a significant improvement in the areas of diagnosis, treatment, disease management, and safety. The NIH recognizes the definition of an EHR developed by the HIMSS:

> The EHR is a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting. Included in this information are patient demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports. The EHR automates and streamlines the clinician's workflow. The EHR has the ability to generate a complete record of a clinical patient encounter - as well as supporting

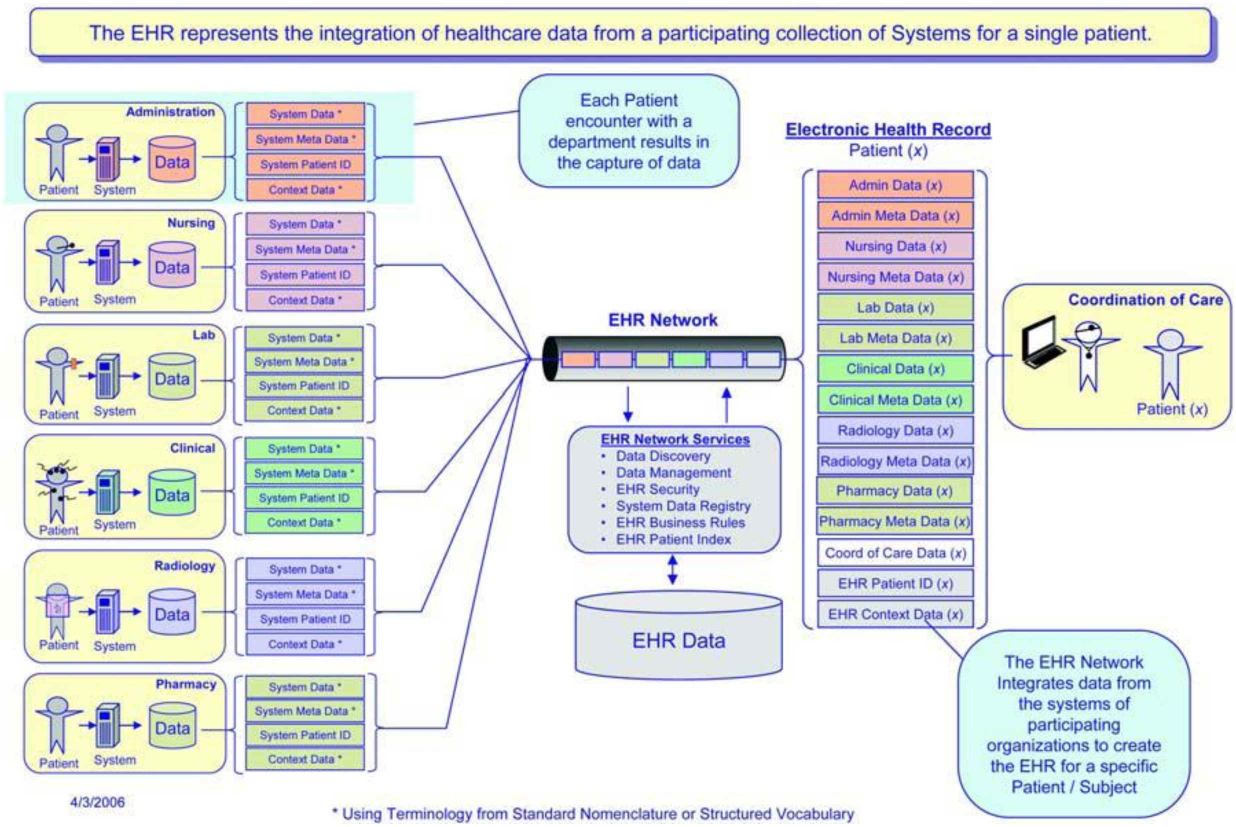
other care-related activities directly or indirectly via interface - including evidence-based decision support, quality management, and outcomes reporting. (2013)

The EHR automates and integrates the continuum of care. The operational portion of the EHR records current and recent encounters. The operational EHR streamlines the administrative process by reducing redundant data entry and combining all treatment (and associated costs) under a patient ID located in the master patient index. The clinical portion of the EHR augments the treatment process by presenting the provider with patient baselines and trends from symptoms, tests, and treatments. The EHR enhances safety through the electronic ordering of medications and treatments, as well as providing alerts for medication errors and abnormal test results.

A fully interoperable EHR enables a secure, electronic means of sharing clinical data inter-organization through regionally organized health information exchanges. This capability decreases duplicate laboratory and radiological testing which streamlines the diagnosis and treatment process. The RAND Corporation estimates that nationwide adoption of the EHR could save approximately $813 billion per year and prevent 200,000 adverse drug events across the healthcare industry, but the short-term implementation costs are close to $100 billion which are borne by the local HCO (Girosi, Meili, & Scoville, 2005).

The EHR looks across a wide range of care (see Figure 2). It combines administrative services, ancillary services, clinical care, and research. Computerized Provider Order Entry (CPOE), a component of the EHR, enables providers to electronically enter physician orders, replacing order sheets and paper slips, which

Figure 2. EHR – Conceptual Overview



Source: MITRE Corporation, 2006.

overcomes problems associated with illegibility. The American Hospital Association collects data on the implementation of five varieties of CPOE: Medication, laboratory, diagnostic imaging, referrals, and nursing notes (2011). Each variety adds another dimension of capability for the provider to provide better, more efficient care.

One of CPOE's subcomponents, Clinical Decision Support Systems (CDSS), also provides medication alerts and presents test results. The CDSS subcomponent can also assist providers with diagnosis recommendation, disease management, and treatment options vetted through recent research. Most EHRs use a standardized vocabulary to normalize medical terminology and phrases, such as "leucopenia" = "low white count" and "hypertension" = "high blood pressure." The standardized vocabulary not only bridges care between providers, but it also aids with billing by aligning internationally recognized code sets such as ICD-10, CPT-10 codes, and HL7 standards of interoperability. Clinical care is captured and integrated into the EHR through electronic flow sheets, structured templates, patient assessment, and clinical reports such as discharge summaries. Figure 2 also illustrates the robust and pervasive nature of the EHR, and it shows how EHR adoption can affect all aspects of an HCO. EHR implementation changes the approach and business of medicine (MITRE, 2006).

EHR Adoption

The SR effects of EHR implementation consume an HCO's organizational strategy due to cost, training, and disruption. The HIMSS (2013) provides an online guide on EHR adoption. This guide details the Davies Award criteria and instructs organizations to include the organizational strategy team on EHR implementation. The HIMSS insists that EHR implementation must include governance to ensure senior-level buy in, it must meet the needs of users and the objectives of the organization, and it must provide benefit to the organization, clinicians, and patients.

The EHR implementation strategy can serve as a disruption to daily operations. Executives should plan for this additional disruption and should include the expectations in EHR training. The EHR implementation changes business practices, administrative financial processes, and clinician routines. The HCO's management should document these changes in both policy and procedure.

Adoption Progress of the EHR

This chapter does a good job summarizing an EHR paradox and a reason for the market failure in relation to EHR adoption. The positive externalities associated with

EHR adoption (safety and efficiency) are not rewarded by the market. The patient and payors are the direct beneficiaries but they are not involved in EHR implementation or maintenance. The market does not directly reward the HCO for adopting the EHR, yet the HCO bears the cost and organizational disruption inherent to EHR implementation. These negative externalities of EHR adoption can adversely affect an organization's ability to compete.

At the end of 2009, only 1-1.5%% of US hospitals had adopted a fully integrated EHR (Jha et al., 2009; HIMSS, 2013). This low rate of diffusion casts doubt on the notion that hospitals can realistically reach full implementation by the original Presidential goal of 2014. It also helps to explain why the sitting President's timeline for implementation has been moved to 2018. Studies on EHR implementation should enable HCOs to implement EHR solutions more efficiently and with minimal disruption to high-quality patient care.

CHAPTER 3: Literature Review

Literature Similar to this Study

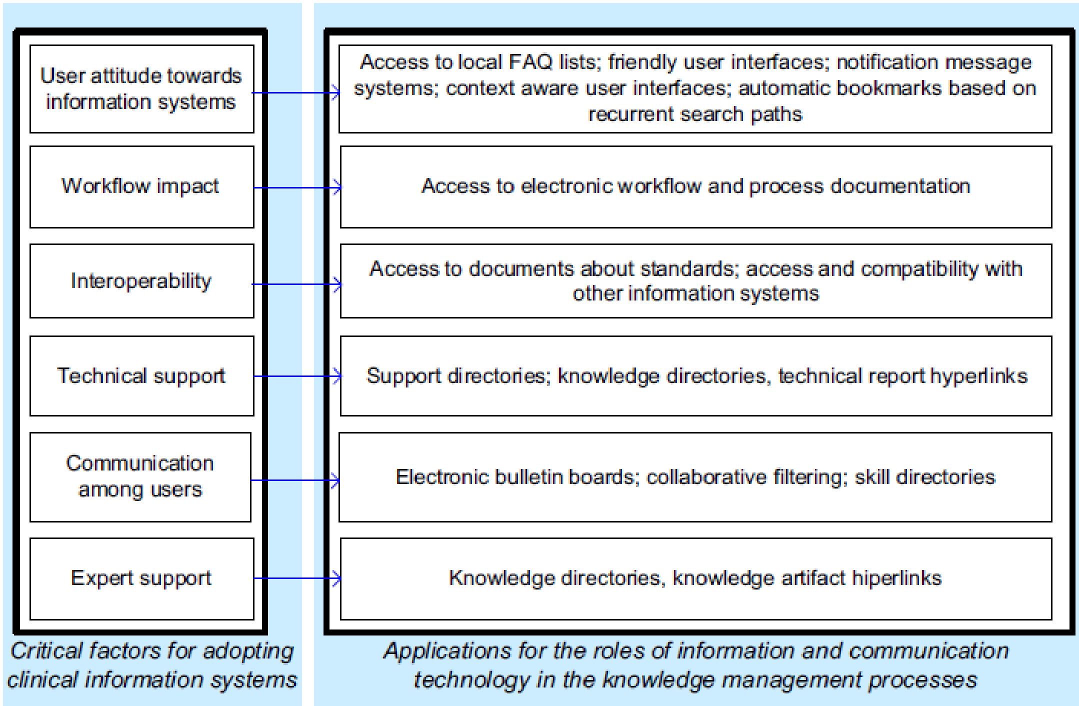
Ash and Bates (2005) examined EHR adoption rates and the factors and forces affecting system adoption. They surveyed 1,000 hospitals from the 6,000 listed in the AHA guide and received a 65% response rate. Although only 16.3% adopted some form of EHR, 59% of these hospitals implemented a full CPOE solution, and the other 41% implemented a partial CPOE solution. A full one third of adopters were either Veterans Affairs or military hospitals. Additionally, 74% of those who planned to implement a full solution intended to do so within five years. Ash and Bates also found that the size of hospital is positively associated with component adoption: Specifically CPOE adoption. Similar studies in other western countries show that the primary purpose of EHR functionalities is to document the clinical encounter and write prescriptions. Ash and Bates inferred from their results that one of the primary reasons to adopt the EHR is to gain the quality-of-care advantages of CPOE.

Wang et al., (2005) studied the factors that influence health information system (HIS) adoption in American hospitals. The authors analyzed a cross-sectional sample of secondary data from multiple sources (n=1441). Results showed that HIS adoption is influenced by the hospital market, organizational and financial factors. Larger, system-affiliated, and for-profit hospitals with more preferred provider organization contracts are more likely to adopt managerial information systems than other hospitals. Operating revenue is positively associated with HIS adoption. The study also identified hostility as an aspect of environmental uncertainty, and that organizations often turn to technological adoption to regain competitive advantage.

Castillo, Martinez, and Pulido (2010) researched a knowledge-based taxonomy of critical factors for adopting an EHR. They analyzed multiple sources of secondary data (n=68) to identify six factors. The study is an extended literature review of 2,920 articles from scholarly sources. The authors found six significant adoption factors, listed in order of importance: User attitude towards information systems, workflow impact, interoperability, technical support, communication among users, and expert support. Figure 3 illustrates additional details and relationships between the six critical factors.

Blavin, Buntin, & Friedman (2010) studied alternative measures of EHR adoption among hospitals. The authors analyzed a 2009 information technology supplement survey distributed by the AHA. The survey focused on 24 EHR functionalities in various areas: Electronic clinical documentation, results viewing, CPOE, and clinical decision support. The researchers used a binary variable of 0 for no functionalities, and 1 for all 24. They also created a second measure with a range of functionalities, 0 – 24. Through factor analysis, they found that 3.6% of hospitals have implemented all 24 functions, 9.8% of hospitals have implemented at least 20 functions, and 36.5% have implemented at least half of the functions. The researchers added that EHR adoption is a complex process.

Figure 3. Relationship Among Critical Factors for Adopting the EHR



Source: Castillo, Martinez, & Pulido (2010).

Ginn, Shen, and Moseley (2011) studied the relationship between hospital financial position and the adoption of the EHR. Through a cross-sectional study of secondary data from several sources, including the AHA, (n=2,442) the authors identified five independent and one dependent variable. Of the five independent variables, only liquidity was positively associated with EHR. Asset turnover was negatively associated with EHR adoption. Bed size, a control variable, was positively associated with EHR adoption. The authors concluded that hospitals adopt EHRs as a strategic move to better align themselves with their environment.

Farley and Hogan (1990) assessed variables of hospital influence in five categories: (a) capacity as measured by number of beds in groupings by intervals of

100, (b) management, or ownership, (c) organizational focus, or teaching status, (d) competitive location and alternatives, and (e) state regulatory pressures. Several of these measures from Farley and Hogan are used in this study.

This study combines the influences highlighted by previous work and examines determinants of HIT adoption. Examining HIT adoption at the HCO level will demonstrate validity between this study and others that have used the hospital as the unit of analysis. This study does not intend to posit an ideal model of HIT adoption, but instead uses different units of analysis to examine the effects of internal and external influences on hospitals that have already adopted the EHR.

Organizational Theories Pertinent to This Study

Several organizational theories address portions of the conceptual model depicted in Figure 2, but none of these are adequate to fully address the complexity of the HCO. Payers, providers, patients all control resources that exert influence. The nature of the competitive environment will also exert influence on decisions. External influence from those who control resources can be explained through Resource Dependence Theory. Internal and external influences can be explained by the Diffusion of Innovation Theory through its introduction of *compatibility, complexity, trialability, observability,* and *relative advantage*. This study combines a portion of these theories into a hybrid that I will just call the *Kruse Theory*.

According to resource dependence theory, healthcare organizations with the greatest level of dependence on other organizations that control the resources will feel the greatest level of environmental influence on its decisions (Pfeffer & Salancik, 1978). The Resource Dependence Theory describes an external interdependence of organizations. *External Control of Organizations*, (Pfeffer & Salancik), which is an adaptation of Resource Dependence Theory, provides good insight for this study. The authors' premise is that the external environment creates a social context and plays an important role in how organizational decisions are made. The lack of absolute independence requires some degree of inter-organizational exchange of goods or services (Pfeffer & Salancik). As organizations build and negotiate relationships with each other in the exchange of resources, positions of power are established. No one organization can provide all of its own resources, so each organization becomes dependent on the other organizations that control the resources.

Similar to Resource Dependence, the Diffusion of Innovation Theory describes a social system that influences through communication channels (Rogers, 1962, 1995, 2003). Diffusion of Innovation attempts to explain how "an *innovation*, is *communicated* through *channels over time* among members of a *social system*" (2003, p. 36). Rogers accounts for 49-97% of variance in the rate of adoption of innovation through five factors: *Compatibility, complexity, trialability, observability,* and *relative advantage.* These factors are sorted into three categories of a predictive model for EHR adoption: innovation determinants, organizational determinants, and environmental determinants. (2003, p. 221). These five factors will each be explored.

Rogers' (2003) concept of *compatibility* goes beyond answering the question, "is a product/service right for a market?" It also asks, "Is the market ready for the product/service" (p. 241)? For instance, the Chevy Nova failed in Spanish-speaking markets because in Spanish the word "Nova" means "does not go" (p. 251). Promotion of conservation techniques to farmers in America initially failed because farmers associated conservation with lower crop yield. Boiling water to sanitize it makes perfect sense to a market that is familiar with germ theory, but primitive tribes in Peru only heated water for sicker, weaker members; as a result, the concept failed when initially introduced and dysentery continued to flourish. In relation to this study, the concept of compatibility might ask, “Is the market ready for the EHR?”

Rogers’ (2003) concept of *complexity* is highly appropriate to this study because innovation can be a double-edged sword: On one hand, it is new and may offer some improvement to a product or service. However, it might also be perceived as too complex; and perception can be a powerful force (p. 257). If the Baby Boomer generation perceives computers to be too complex, and this perception causes computer anxiety, its users may reject its adoption and use (Czaja , Charness, Fisk, Nair, Rogers, & Sharrit, 2006). The older physicians in a hospital have greater seniority, and are therefore, more influential in the hospital’s decision to adopt the EHR. Would this same generation of providers influence the HCO considering EHR adoption?

Rogers’ (2003) concept of *trialability* applies more to the *early adopter* group than other groups. In the early phase of promotion for a new product or service, the vendor might lower the risk of adoption by offering free trials or samples to potential users. Once the user is confident of the new item’s efficacy, then he/she is more likely to pay full price for its use (p. 258).

Roger’s (2003) *observability* is also highly applicable to this study (p. 258). Decision makers in a hospital that has not yet adopted an EHR will observe the experiences of other hospitals that have adopted it. Vendors will promote or advertise specifically to the non-adopters and help them observe how the EHR can benefit its organization. External players in the HCO's competitive environment will provide some level of observability.

Relative advantage is a multifaceted concept for this study. In healthcare, the most important factor is provision of health, as well as the treatment and prevention of disease. If adoption of the EHR speaks directly to the HCO's primary purpose, then it might provide relative advantage over competitors that have not adopted it. Rogers also addresses the concept of social prestige. Unless an HCO can serve as an example to other HCOs (observability), there may not be a sufficient level of relative advantage to be considered.

CHAPTER 4: Theoretical Framework

This chapter will develop the Kruse Theory that evaluates the external and internal environmental influences on organizational strategy of HCOs that adopt the EHR. The literature is full of models and theories developed to evaluate corporate decision making, strategic management, and technology acceptance. The complexity of the HCO needs a complex theory that combines multiple traditional theories to identify and evaluate the factors that influence the decisions of the healthcare organization.

EHR Adoption and Environmental Influence

Several influences in the environment exert pressure on the HCO to adopt the EHR. Influences range from incentives from the federal government to the nature of local competitive community. Federal incentives provide a heavy influence for EHR implementation, under specific conditions, and penalties for a lack of EHR implementation.

The US Government passed the Health Information Technology for Economic and Clinical Health Act (HITECH, 2009) to incentivize EHR adoption and assuage the SR effects of cost to the HCO. Objectives of EHR adoption are placed into three stages of gradually increasing levels of EHR implementation. The following paragraph summarizes the objectives of the first stage.

The focus of Stage 1 is the adoption of basic EHR capabilities to include CPOE, CDSS, alerts, reminders, and electronic communication. Table 1 summarizes the criteria used to measure achievement of the objectives in Stage 1 (42 CFR, Vol 70

Table 1.

Summary of Stage 1 Criteria for Meaningful Use of EHR

Stage 1 (Adopt basic EHR capabilities & practices)
>10% pts receive patient-specific education resources
>30% pts $\geq$ 1 med through CPOE
>40% scripts transmitted through certified EHR
>50% demographics recorded through structured data
>50% have ht, wt, bp recorded as structured data
>80% pts $\geq$ 1 problem recorded as structured data
>50% pts receive an electronic copy of records (upon request) and clinical summaries within 3 bus days
Implement one CDSS rule
Perform $\geq$ 1 test of certified EHR capacity to electronically transmit clinical information
100% Drug alerts provided electronically

(140)). The Federal Register proposes objectives for Stages 2. It is an expansion of the Stage 1 objective to exchange clinical data securely (45 CFR, Vol 77 (13698)). Stage 2 criteria require organizations to adopt a more robust ability to exchange information through transitions of care, it requires that hospitals have the ability to provide a patient with an electronic copy of his/her medical record, and that hospitals use HIT to report continuous quality improvement at the point of care. Specific criteria for Stage 3 have not yet been published, but they are expected to focus on the integration of CDSS capabilities toward national health goals. The HITECH Act also publishes a timeline for HCOs to qualify for monetary incentives. This timeline, illustrated in Table 2, shows the gradual implementation schedule and the overall deadline of 2014.

Table 2.

Timeline for Implementation of Meaningful Use Criteria

First Payment Year	Payment Year 2011	2012	2013	2014	2015
2011	Stage 1	Stage 1	Stage 2	Stage 2	TBD
2012		Stage 1	Stage 1	Stage 2	TBD
2013			Stage 1	Stage 1	TBD
2014				Stage 1	TBD

The internal politics of one organization serve as one source of influence. A hospital is part of a community, which serves as an external influence. Further, if a hospital is also part of a larger multi-hospital system (MHS), then the politics of the broad MHS will also exert influence on local decisions.

Environmental Influence and Organizational Strategy

Strategy can be a multifaceted concept, and organizations around the world hire strategy experts to help identify and focus on a market forces. An operational definition of strategy is borrowed from Fumasoli and Lepori (2011) and is adapted to healthcare: Strategy is defined as instruments by which *HCOs* manage their organizational processes and deal with their environments in order to select a portfolio of activities and find appropriate position in the *healthcare industry*.[4] It follows that adoption of an EHR would alter how an HCO manages its organizational processes, so the authors' definition of strategy is a good fit for the healthcare industry. However, two significant considerations in the healthcare environment are the level of local competiveness, and how HCOs compete (Sikka, Luke, & Ozcan, 2009).

[4] Italics indicate a change in wording from the authors' definition. The intent of the change is to modify it from a general business definition to one that is specific to the healthcare industry.

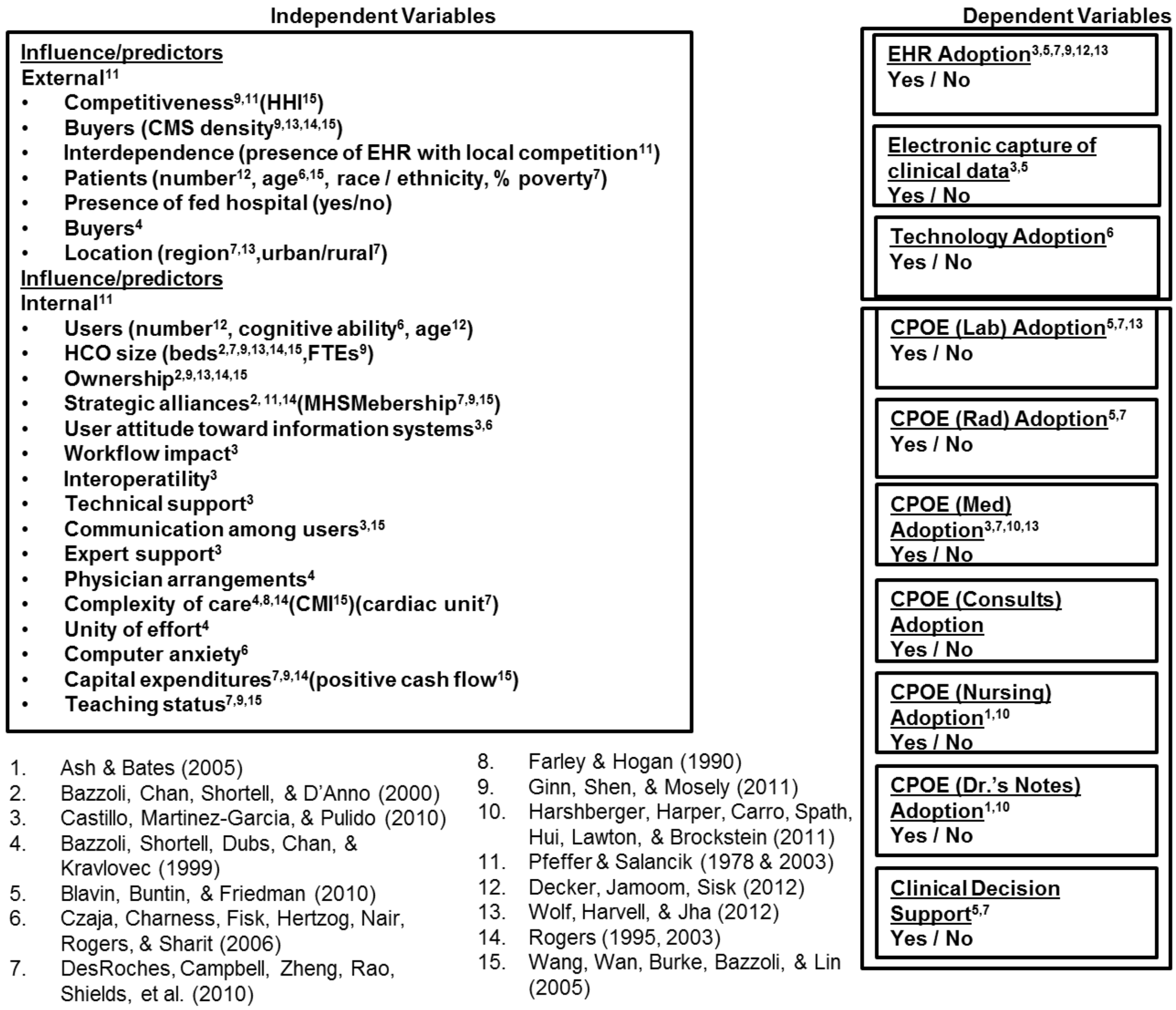
Studies have shown that decision making in the healthcare industry is often based on how the organization competes, whether in a single market or multi-market environment. In either environment, decision-making varies on competition, and the healthcare industry competes in clusters (Bazzoli et al.,1999). The way HCOs compete will also affect its organizational structure. Bazzoli et al., identifies a reliable, internally valid, and stable four-cluster solution for health networks and a five-cluster solution for health systems. Differentiation and centralization are particularly important in distinguishing unique clusters of organizations. High differentiation typically occurs with low centralization, which suggests that a broader scope of activity is more difficult to centrally coordinate. Integration is also important, but the authors find that health networks and systems typically engage in both ownership-based and contractual-based integration or they are not integrated at all.

The environment of healthcare is unique in a competitive environment. The HCO develops an organizational strategy based on the local environment. To increase an organization's ability to compete, its strategy might also include cost reduction, and EHR adoption runs counter to this goal in the SR. Studies estimate that adoption of the EHR could eventually save more than $813 billion annually, prevent 200,000 adverse drug events, and enhance the doctor-patient relationship through increased communication (Hillestad et al., 2005; RAND, 2005). Unfortunately, these benefits are realized in the LR, while the investment to adopt the EHR is expended in the SR. A large SR deficit could inhibit an HCO's ability to compete or survive in heavily competitive environment. The HIMSS (2009) confirms that the primary obstacles that prevent immediate adoption are cost and complicated implementation.

Presentation of Conceptual Model of the Kruse Theory

The conceptual model for the Kruse Theory is illustrated in Figure 4.

Figure 4. Conceptual Model Used for the Kruse Theory



This framework captures both internal and external factors that influence the adoption of the EHR. The Kruse Theory is developed from aspects of multiple theories such as Diffusion of Innovation and Resource Dependence. The premise is that environmental influences affect organizational strategy of HCOs that adopt the EHR.

Rogers' (1995) Diffusion of Innovation theory provides three categories of a predictive model for EHR adoption: Innovation determinants, organizational determinants, and environmental determinants. Pfeffer and Salancik's (1978) Resource Dependence theory provides a category of a predictive model for EHR adoption: The competitive environment. In construction of the Kruse Theory, several constructs emerged.

The patient primarily serves as an external influence. Although some employees of the HCO might also be patients and this relationship could create a small internal influence, this study considers those stake holders in the internal organizational factor of provider users. The providers serve as an internal organizational influence. The payer is a significant influence. The CMS serves as a good example of this significant influence. The HITECH Act provides monetary incentives for EHR adoption. Those who do not implement all aspects specified in the stages of adoption are not eligible for the incentives. In this way, the CMS disincentivizes those organizations that do not adopt the EHR. If payments from the CMS were of little consequence to the HCO's revenue, then the HCO might decide differently about EHR adoption. A competing HCO is an external market force in the environment. Third-party payers might compare HCOs based on maturity of automation because mature clinical components like CPOE will result in more accurate billing. Such forces incentivize an HCO to adopt the EHR.

There is overlap between the sources / theories. There are four internal forces and seven external forces identified by three authors: Rogers, 1995 & 2003, Pfeffer and Sanancik, 1978 & 2003, and Wang et al., 2005. However it is unclear in existing literature the degree to which these forces can influence an HCO's decision to adopt the

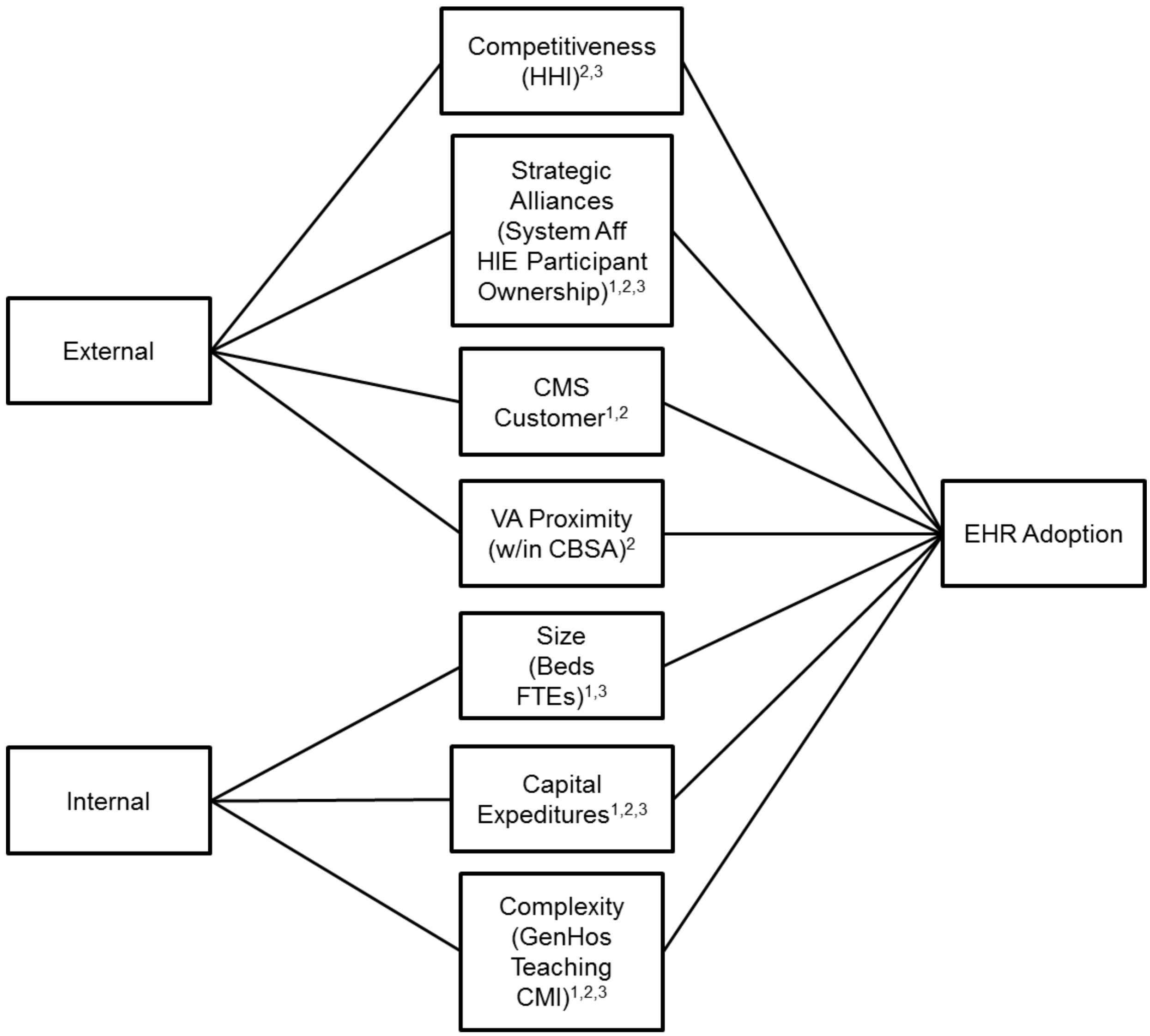
EHR. A complex organizational theory should provide insight into the strength of the influence on the complex HCO. Figure 5 illustrates the combination of these models into the Kruse Theory which will identify and evaluate the external environmental and internal organizational factors that influences an HCO's decision to adopt the EHR. Figure 6 applies this model to CPOE adoption.

Examining HIT adoption at the individual facility might ignore the other influences on such an important strategic decision. This study, however, includes these other influences by examining determinants of HIT adoption. Examining HIT adoption at the facility level will demonstrate validity between this study and others that have used the hospital as the unit of analysis. Finally, examining the determinants of HIT adoption at the community cluster level taking into consideration the MHS membership will provide the most complete picture of HIT adoption. This study does not intend to posit an ideal model of HIT adoption, but instead uses different units of analysis to examine the internal and external influences on hospitals that have already adopted the EHR.

Development of Hypotheses

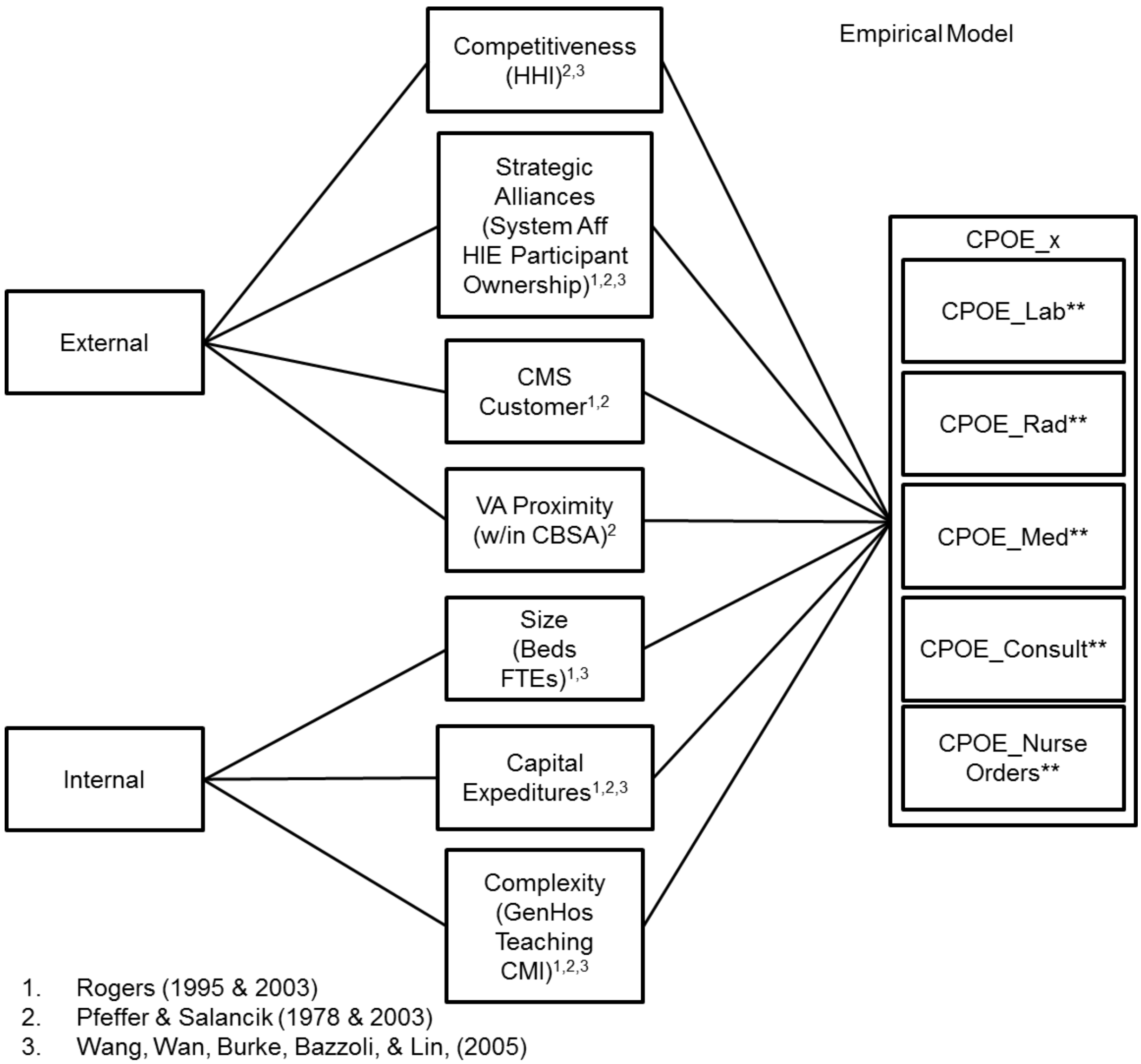
The combination of the work from Pfeffer & Salancik (1978), Rogers (1995 & 2003), and Wang et al., (2005) all identify external forces in the environment and internal organizational forces of the HCO that exert influence. Multiple studies evaluating HIT adoption use the individual hospital as the unit of analysis; the HIMSS Electronic Medical Record Adoption Model serves as a good example (see Appendices A & B). These studies have good methodology, but their choice of the unit of analysis overlooks the proximal nature of competition. Hospitals compete locally and therefore

Figure 5. Empirical Model Used for the Kruse Theory (EHR)



1. Rogers (1995 & 2003)
2. Pfeffer & Salancik (1978 & 2003)
3. Wang, Wan, Burke, Bazzoli, & Lin, (2005)

Figure 6. Empirical Model Used for the Kruse Theory (CPOE)



make strategic decisions based on local interdependence, which is defined as a reciprocal relationship between distinct but mutually dependent entities (Porter, 1998).

The HHI measures local competitiveness, and is therefore the first variable chosen for the Kruse Theory. An investigation into the relationship between hospital adoption of the EHR and market, operating, and financial characteristics may identify salient, triggering, or influencing determinants. While the existing literature is helpful in analyzing hospital adoption of cost accounting systems and high tech equipment, little has been published on the factors that contribute to the adoption of the EHR and specific components of the EHR. The secondary analysis from this study looks specifically at CPOE to evaluate component adoption.

Nine hypotheses are developed to assess a predictive relationship of EHR adoption with market, organizational, and financial forces. Wang et al., (2005) identify hostility as an aspect of environmental uncertainty, and that the organization's reaction to hostility is often realized in technological adoption to gain competitive advantage. The authors use the measure of competitiveness to measure the existence of hostility and the organizational response. The key market force at play is competitiveness. Thus, it is postulated:

H1: Holding all other factors constant, HCOs that operate in competitive environments will be more likely to adopt the EHR.

Diffusion of Innovation theory relies heavily on communication channels to promulgate the innovation. Communication is enabled both within and external to the HCO. The HCOs that participate in hospital alliances would be more keenly aware of the diffusion of the EHR. Thus, it is postulated:

H2: Holding all other factors constant, HCOs that participate in strategic hospital alliances will be more likely to adopt the EHR.

Resource Dependence theory speaks of the interdependence of organizations. Resources serve as a source of power or leverage over other organizations. Federal incentives for the adoption of the EHR specifically address those HCOs that provide care to populations covered by the CMS, therefore HCOs that are more dependent on the CMS for their revenue stream are subject to the influence of federal incentives. Thus, it is postulated:

H3: Holding all other factors constant, HCOs that service Medicaid/Medicare populations will be more likely to adopt the EHR.

Jha, et al. (2001) points out that VA hospitals are the most common adopters of the EHR. Because competitors tend to mimic each other, it is postulated:

H4: Holding all other factors constant, HCOs with a VA hospital serving as a local competitor will be more likely to adopt the EHR.

Diffusion of Innovation theory also posits that organizations with excess resources will be more likely to adopt innovations. Larger organizations typically have access to more resources than smaller organizations. Such organizations are better equipped to evaluate, develop, and adopt innovations. In addition to Farley and Hogan (1990), Zwangziger et al. (1996) used bed size as a significant factor. Thus, it is postulated:

H5: Holding all other factors constant, HCO size will be positively associated with EHR adoption.

HCOs that deliver complex and specialized care typically need the use of innovation to provide the services and coordination of care. The use of IT enhances the HCO's ability to manage the complexity of care and specialized services, teaching activities, and coordinated care (Chau & Tam, 2000; Renshaw, Kimberly, & Schwartz, 1990). Thus, it is postulated:

H6: Holding all other factors constant, HCOs that coordinate complex care will be more likely to adopt the EHR.

Both the Diffusion of Innovation theory and Resource Dependence address the cash flow status of the organization. Those organizations with greater access to capital would be more likely to accept short-term risk associated with EHR adoption. Thus, it is postulated:

H7 Holding all other factors constant, HCOs with positive cash flow will be more likely to adopt the EHR.

Combining the effects of competitiveness and the incentives from the CMS to adopt the EHR, the external influences should outweigh internal. Thus it is postulated.:

H8: Holding all other factors constant, External sources will influence an HCO to adopt the EHR.

Because authors have previously postulated that organizations adopt the EHR for the quality-of-care advantages of CPOE, there should be evidence to support the idea. A secondary analysis is performed: It is postulated:

H9: Holding all other factors constant, HCOs that adopt the EHR will also adopt key components of CPOE[5]*.*

[5] N.B., this hypothesis is phase two of the study. It uses EHR adoption as the IV and CPOE-adoption as the DV in a secondary analysis. Analysis is performed on each variety of CPOE: Laboratory, radiology, medication, consultations, and nursing notes.

CHAPTER 5: Methodology

Research Design

This study meets the definition of a non-experimental, cross-sectional research design. The literature review found that in general, researchers using secondary data evaluated larger sample sizes than those using survey instruments. The two exceptions to this generalization are Menachemi, Prickett, & Brooks, (2011) and DesRoches et al., (2010) which analyzed 6260 and 2758 surveys, respectively. Secondary data samples were generally above 2000. This study will follow their example of analyzing secondary data. An $\alpha<.10$ is chosen because this is an exploratory study and overall EHR adoption is low.

Data Sources

Secondary data are analyzed from two independent sources: American Hospital Association and the Center for Medicare and Medicaid Services. The data from the AHA (2009) exclusively identify five of the seven independent variables and partially identify one other. Tables 3 & 4 illustrates the external and internal variables chosen from the conceptual model. The database from the American Hospital Association was used by Bazzoli, et al. (1999) and Sikka, et al. (2009). Their analysis of HCOs across the US is important to this study because it combines individual variables into a

Table 3.

Variable-to-Data Map (External Environmental Influences)

Source of influence	Variable		Measure	Data source	Data type	Data transformation
X_8 External Environmental Factors	Competitiveness	x_1	Herfindahl index	AHA	Continous	
	Strategic alliances	x_{2a}	System affiliation	AHA	Binary	1=Y, 0=N
		x_{2b}	HIE participation	AHA EHR	Binary	1=Y, 0=N
		x_{2c} x_{2d}	Ownership (control)	AHA	Categorical	government **nongov, not-for-profit** investor-owned, for-profit
					w/ dummy variables	1=Y, 0=N
	CMS Recipient	x_3	totcms/admtot	AHA	Continous	
	VA locally	x_4	VA within CBSA	AHA	Binary	1=Y, 0=N

Table 4.

Variable-to-Data Map (Internal Organizational Influences)

Source of influence	Variable		Measure	Data source	Data type	Data transformation
x_8 Internal Organizational Factors	Size	x_{5a} x_{5b} x_{5c} x_{5d} x_{5e} x_{5f} x_{5g}	Bed size	AHA	Categorical	6 - 24 beds 25 - 49 50 - 99 100 - 199 200 - 299 300 - 399 400 - 499 **500 -**
					w/ dummy variables	1=Y, 0=N
		x_{5h}	Number FTEs	AHA	Continuous	Violated Multicollinearity Used Ln
	Complex care	x_{6a}	General medical and surgical (adult) care hospital	AHA	Binary	1=Y, 0=N
		x_{6b}	Teaching status	AHA	Binary	1=Y, 0=N
		x_{6c}	Case mix	CMS	Continous	
	Positive cash flow	x_7	Capital expenditures	AHA	Continous	removed negative numbers
						Violated Multicollinearity Used Ln

composite independent variable. Their study identifies the health clusters in the US and associated competitive strategy. In a similar manner, this study combines several variables into composite variables (size, complexity of care, strategic alliances, and CPOE). The data from the AHA contained four categories of ownership, one of which was named federal. This group contained only three cases so it was combined with the group named *government, non-* federal. The final categories for Ownership are: Government, non-governmental not-for-profit, and independently-owned for-profit. Consistent with hypothesis 2, non-governmental not-for-profit was used as the reference group because, more than the other categories, communication channels between these hospitals should be higher and diffusion would follow. For-profit competition would interfere with communication between for-profit hospitals, and governmental politics would interfere with communication between state hospitals or between federal and state.

The American Hospital Association manages a database comprised of more than 6,000 hospitals and over 450 healthcare systems. The database contains a little over 700 data points per hospital, tracking and trending information such as organizational structure, financial performance, services provided, and personnel. Beginning in 2008, the AHA also included a separate survey to further delineate EHR adoption; it was called the HIT Supplement. Dependent variables for both phases of this study are also gathered from the AHA data (see Table 5). Data from both of the AHA datasets are compiled from annual self-report surveys.

Table 5.

Variable-to-Data Map (DVs in Primary and Secondary Phases)

Phase of study	Variable		Measure	Data source	Data type	Data transformation
Phase I	EHR adoption	Y_1	Adopt an electronic health record	AHA	Binary	1=Y, 0=N
Phase II	CPOE	Y_{2a}	Laboratory	AHA EHR	Binary	1,2=1, else=0
		Y_{2b}	Radiology	AHA EHR	Binary	1,2=1, else=0
		Y_{2c}	Medications	AHA EHR	Binary	1,2=1, else=0
		Y_{2d}	Consultation requests	AHA EHR	Binary	1,2=1, else=0
		Y_{2e}	Nursing orders	AHA EHR	Binary	1,2=1, else=0

The CMS publishes a case mix index (CMI) for all US hospitals that provide care covered by the CMS[6]. This file contains FY 2009 hospitals' CMI for discharges. A hospital's CMI represents the average diagnosis-related group (DRG) relative weight for that hospital. It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges.

Measurement of Variables

I combined data sets on common fields, appropriately coded the binary data, and used Predictive Analytics Software (PASW) – formerly known as Statistical Program for the Social Sciences (SPSS) – to calculate statistical significance. A listwise approach is used to handle missing data.

The AHA annual survey collects administrative data and asks questions. Responses range from continuous to binary. The yes/no questions contained great variance in responses. The data dictionary that accompanied the data coded some yes/no questions as 1=yes, 2=no, and other questions were coded 0=no, 1=yes. The coding of the critical question (has your hospital adopted an electronic health record?) is an area of confusion. The data dictionary for this field was blank. The question offered three responses: Fully adopted, partially adopted, and not adopted. It took a call to an AHA database administrator to determine the final coding: 0=not adopted, 1=partially adopted, and 2=fully adopted. Table 6 illustrates the results.

---

[6] Data were downloaded on October 29, 2012 from http://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/FY-2011-IPPS-Final-Rule-Home-Page-Items/CMS1237932.html

Table 6.

Responses for EHLTH in AHA Annual Survey

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	EHR not implemented	253	11.7	13.0	13.0
	EHR partially implemented	1239	57.4	63.8	76.8
	EHR fully implemented	451	20.9	23.2	100.0
	Total	1943	90.1	100.0	
Missing	System	214	9.9		
Total		2157	100.0		

The partially and fully adopted groups are combined into one. The binary responses limit the choices of statistical tests for statistical significance, but recoding to a consistent response will at least enable a higher level of validity

Logistic regression is a good fit for this study because it requires that the dependent variable be categorical, and it does not require the independent variable to be multivariate normal. Proper coding is necessary. This study calculates the association that EHR adopters are large hospitals (beds & FTEs), with large expenditures, that provide complex care (General, teaching hospital, & high CMI), that are members of strategic alliances (System affiliation, HIE participation, & Ownership), that receive reimbursement from the CMS, and are proximately located to a VA facility. Using the AHA database enables the selection of a large sample size. The test statistic is the chi-square test for the overall model of goodness of fit.

Nineteen measures for seven independent variables are identified from the data sets. Tables 3-5 map the variable to its measure(s); and it identifies the data field and corresponding data source. The *Competitiveness* variable is composed of one measure: The Herfindahl index. This Index, also known as the Herfindahl–Hirschman Index (HHI), measures the firm's contribution to the industry. Economists use this index to measure competitiveness of an industry. The resulting index shows the firm's market share weighted by the productivity of the local industry. In healthcare, the index is calculated by overall patient days of the hospital compared to that of the region in which it resides. Despite the unusual distribution (Appendix C), the literature does not show that previous research used data transformations on this field, and a great deal of research used this data field as a continuous variable. Based on Hypothesis 1, the highest index should reflect highly competitive markets, and greater external environmental influence to adopt the EHR.

Strategic alliances is a compound variable consisting of three measures: *System Affiliation*, *HIE Participation*, and *Ownership*. The first two measures are binary. The third is categorical. Dummy variables are introduced to accentuate group effects for the categorical variable. Based on Hypothesis 2, the group with the highest level of alliance, non-government not-for-profit, is held as the reference group.

The *CMS population* variable is a calculated measure, *CMS density,* based on total CMS bed days divided by the total bed days of the HCO. This is a continuous variable that ranges from 0 to 1. The highest level of CMS density (in revenue) should equate to the highest level of EHR adoption. Based on Hypothesis 3, the highest level of CMS density should reflect adoption of the EHR.

VA locally is determined through logic. Proximity to a VA facility is identified through the CBSA field from the AHA data. If the CBSA for an HCO is the same as any

VA facility, then the measure is coded with a 1. Otherwise, it is coded as zero. Hypothesis 4 predicts that hospitals within the same CBSA as a VA facility will be more likely to adopt the EHR.

Size is a compound variable consisting of *Bed size and Number of FTEs.* These measures are both ordinal. Dummy variables are introduced to the categorical variable to accentuate group effects. Based on the literature, larger hospitals have larger budgets and are expected to more readily adopt the EHR. Based on Hypothesis 5, the largest hospitals should have greater adoption of the EHR.

Bed size (BSC) is collected as categorical data, but full-time equivalents per hospital (FTEH) are collected as continuous. The group with the largest bed size for BSC was held as reference group. The distribution of the FTEH data is highly unusual (see Appendix C).

Complexity of care is a compound variable consisting of three measures: *General hospital*, *Teaching status*, and *Case mix*. The first two measures are binary and are collected from the AHA data set. The third measure is continuous and is collected from the 2009 Case Mix Index (CMI) from the CMS. The CMI is defined as "the average diagnosis-related group (DRG) relative weight for that hospital. It is calculated by summing the DRG weights for all Medicare discharges and dividing by the number of discharges" (cms.gov, 2012, paragraph 3). Based on Hypothesis 6, the most complex case mix is expected to have the greatest level of EHR adoption.

Positive cash flow is measured by the measure *Capital expenditures* from the AHA data set. It is a continuous variable. Negative values are removed because the literature only evaluates positive cash flow. Based on Hypothesis 7, the HCOs with the largest expenditures should be more likely to adopt the EHR.

All seven independent variables are identified as external or internal, based on the conceptual model. All measures for external influences are compared with results from internal influences. Hypothesis 8 predicts that the external influences will have a greater effect on the association between IVs and DV. This is based on Resource Dependence Theory.

The *EHR adoption* field is the dependent variable in the primary analysis. It is a binary variable collected by the AHA data set. Missing fields were handled by examining the AHA EHR data set. If HCOs reported implementation of any variety of CPOE in at least one location, the *EHR adoption* field is coded as 1[7]. This transformation completes 253 additional cases. The rest are omitted through a listwise approach.

The secondary analysis used only those HCOs that have reported adoption of the EHR (independent variable). The dependent variable consisted of five varieties of CPOE: *Laboratory orders, radiology orders, medication orders, consultation requests,* and *nursing orders.* These measures are taken from the AHA EHR data set and are binary variables. If an HCO reported that it had fully implemented CPOE in at least one location, then it was coded as 1. Otherwise, it was coded as zero.

[7] CPOE is a component of the EHR.

Methods or Procedures for Hypothesis Testing

I cleaned and properly coded the data and ran descriptive statistics to identify mean, standard deviation, frequencies, and outliers (Appendix C). I removed records with missing data elements.

The PASW statistical output will provide a parameter estimate which serves as the *b* coefficient used to predict the logit of the dependent variable.

$$P(Y) = \frac{1}{1+e^{-(b_0 + b_1X_{1i} + b_2X_{2i} + \ldots\ldots + b_nX_{ni})}} \text{ (Field, 2009)}$$

The exponential beta provides an odds ratio of the dependent variable and the probability of the dependent variable is determined from this odds ratio. If the exponential beta is greater than one, then the probability of higher category increases. The measure of effect size is the Nagelkerke R^2.

Exploratory and Confirmatory Analytic Strategies

The AHA data set provides a large amount of data to analyze. Because this study fills a gap in literature, I am exploring the effects of internal and external factors that exert influence on HCOs that adopt the EHR and if EHR adopters also adopt any variety of CPOE. However, in many ways, this study fits more with confirmatory analytic strategy than exploratory. Based on the number of external factors of influence, I predict that external factors will have a greater effect than internal factors.

Potential Problems that May be Encountered

This study analyzes secondary data published by the AHA and the CMS from 2009 surveys and database, respectively. Data are combined and analyzed. A stronger relationship between the independent and dependent variables may be found if additional data sets from the same sources but other years are analyzed. The disadvantage in the approach used in this study is that EHR adoption rates change constantly.

The low EHR adoption rate in 2009 will also present a problem. Missing values account for about 60% of the population. Of those who did participate in the survey, a very low percentage have adopted a fully interoperable EHR (Jha et al., 2009). It may be difficult to generalize to the population based on the responses of so few.

Those hospitals that participate in the HIT supplement survey are most likely ones that have adopted the EHR. Descriptive statistics show that after cases are removed from the study, 75% adopted. This study could overestimate the relationship between adopters and influences because we do not know a reason for those who did not respond. It is assumed, however, that missing data are random and do not serve as a source of bias.

Because the AHA database is primarily composed of binary data, the statistical tests available are limited. This study uses a traditional binary logistic regression to identify the relationship between independent and dependent variables, but this can be limiting in data analysis.

CHAPTER 6: Results

Descriptive Analysis of the Study Variables in the Study Sample

A missing data analysis was performed on the AHA annual survey and the HIT supplement survey. The annual survey showed a high number of missing values for MHSMEMB (42%) and GENHOS (24.3%). Due to the high level of missingness, this study may underestimate the effect of these measures. The analysis for the HIT supplement showed no significant results; the number of missing values was very low. Missing value analysis revealed that the majority of variables had less than 5% of missing data. An analysis to determine differences in "skipped" survey questions was not necessary since the amount of missing data was small (Tabachnick & Fidell, 2007). Table 7 illustrates the results of the missing value analysis on the CPOE data.

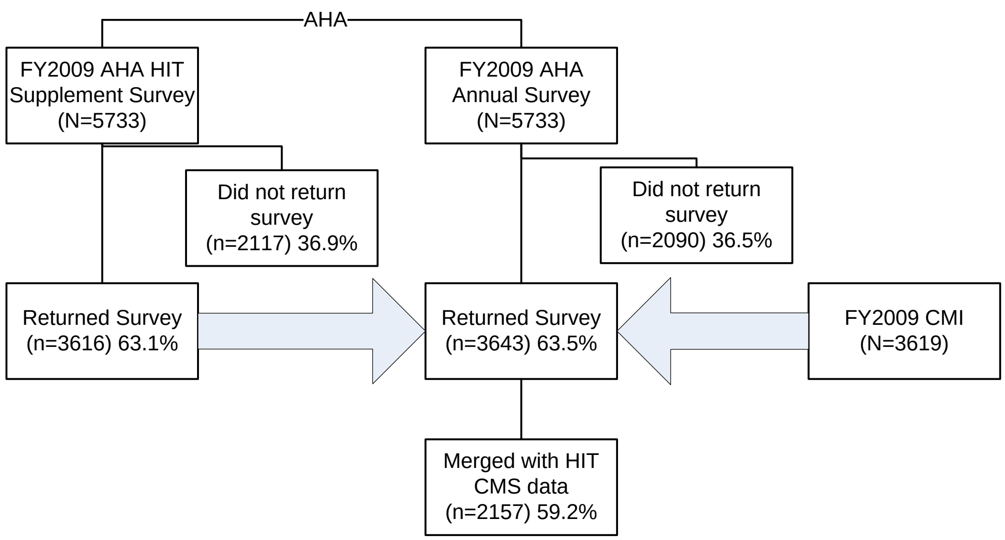
Table 7.

Missing Value Analysis for CPOE Data

	N	Missing	
		Count	Percent
q1_a3	2114	43	2.0
q1_b3	2135	22	1.0
q1_c3	2128	29	1.3
q1_d3	2129	28	1.3
q1_e3	2131	26	1.2

Data from the AHA and the CMS are joined. The CMS data showed three missing values for the measures studied. From the original 5733 in the AHA database, 2157 remain after the data merge. Figure 7 illustrates the inclusion and exclusion criteria (which is expanded in Appendix D).

Figure 7. Inclusion and Exclusion Criteria



The sample I used in this study comprised 24.0% of the population of hospitals in the US. I used the International Hospital Consortium (2009) for the overall number of hospitals. The AHA surveys its registered hospitals annually (n=5773). The AHA adds a hospital to its database if it is accredited as a hospital by the Joint Commission on Accreditation of Healthcare Organizations or is certified as a provider of acute care services under Title 18 of the Social Security Act and has provided the AHA with documents verifying accreditation or certification (AHA, 2013). In 2009, the AHA database was comprised of 5733 HCOs, which represents approximately 85.8% (IHC, 2009). Survey response rates for the annual survey and HIT supplement were 63.5%

and 63.1%, respectively. Data from the two surveys were combined and a listwise approach was used to exclude any case with missing values. The HIT supplement merged with the annual survey with 2157 common cases, but the listwise approach reduced the sample to 1611.

Eight independent variables[8] and one dependent variable are analyzed through a combination of 19 measures in the primary analysis, and the same independent variables and one (CPOE) dependent variable are analyzed through five independently run logistics regressions in the secondary analysis (see Table 3). Twelve measures are binary, five measures are continuous, and two measures are categorical. Descriptive statistics for these measures are listed in Table 8. A description of each variable and its associated measure(s) follows.

The Dependent variable for the primary analysis is EHR adoption (*EHLTH_T2*, n=1943). This variable is binary. In this sample, 78% reported adoption of the EHR.

The variable *Competitiveness* has one measure: *HHI* (N=2157). This is a continuous measure. Descriptive statistics for the Herfindahl indices are illustrated in Appendix C. No data transformations are necessary.

Strategic alliances is a compound variable composed of three measures: *System affiliation (MHSMEMB), HIE participation* and *Ownership*. The hospital's status as a member of a mutli-hospital system (n=2157) is a binary number self-reported in the AHA annual survey. The status as member of an MHS is an established measure of

[8] The eighth variable is the exterior / interior source of influences.

Table 8.

Descriptive Statistics for All Measures

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
EHLTH_T2	1943	0	1	.87	.337
HHI	2157	.0017	1.0000	.2909	.3157
MHSMEMB_T	2157	0	1	.56	.497
HIE_T	2099	0	1	.42	.493
CNTRL	2157	12	47	22.71	5.421
CMS_Density	2157	.00	1.00	.6362	.12587
VA_local	2157	0	1	.43	.495
BSC	2157	1	8	4.55	1.797
FTEH	2157	.0	16423.0	1384.914	1571.2644
GENHOS	1973	0	1	.99	.074
Teach_T	2157	0	1	.10	.305
2009 CMI	2118	.6198	2.8363	1.3930	.2849
CEAMT_T	1738	0.000001M	1469.97M	19.86M	5.11M
CPOE_Lab	2114	.00	1.00	.4257	.49457
CPOE_Rad	2135	.00	1.00	.4197	.49362
CPOE_Med	2128	.00	1.00	.3961	.48921
CPOE_Consults	2129	.00	1.00	.3636	.48113
CPOE_Nursing	2131	.00	1.00	.4266	.49469
Valid N (listwise)	1611				

organizational alliances (Bazzoli et al., 1999). The MHS membership status for the study population ranged from 1-2, 55% of which were members of an MHS. Descriptive statistics are illustrated in Appendix C. Data are transformed from 1-2 to 0-1; in both conditions, “1” is the desired (positive) response.

As outlined in the HITECH Act (2009), a hospital should adopt a fully interoperable EHR and participate in a local or statewide Health Information Exchange (HIE, n=2099). Hospitals report their participation in the AHA EHR Adoption survey. The measure *HIE participation* ranges from 1-2, 43% of which report participation in an

HIE. Descriptive statistics are illustrated in Appendix C. Data are transformed from 1-2 to 0-1; in both conditions, "1" is the desired (positive) response.

The measure of *Ownership (CNTRL)* is collected by the AHA annual survey as a categorical variable (n=2157). Codes range from 12-48 (see Table 9): They are

Table 9.

Ownership Groupings

Code	**Description**	**Recode**
Government, Nonfederal		1,0
12	State	4
13	County	4
14	City	4
15	City-county	4
16	Hospital district or authority	4
Nongovernment, not-for-profit		1,0
21	Church operated	2
22	Non-government-nonprofit Catholic controlled	2
23	Other not-for-profit	2
Investor-owned (for-profit)		1,0
30	Investor-owned for-profit	3
31	Individual	3
32	Partnership	3
Government, federal		1,0
41	Air Force	4
42	Army	4
43	Navy	4
44	Public Health Service other than 47	4
45	Veterans Affairs	4
46	Federal other than 41-45, 47-48	4
47	Public Health Service Indian Service	4
48	Department of Justice	4

discrete, non-adjacent, and non-continuous. The non-government not-for-profit hospital group is held as the reference group.

The variable *CMS recipient* is comprised of one measure, *CMS density* (n=2157). It is calculated by dividing the CMS admissions by total admissions from the AHA data. This is a continuous field (percentage) ranging from 0-1.

Hypothesis 4 is tested through the measure VA_locally comprised of one measure, *VA_local* (n=2157). It is a binary measure coded as 1 if a VA facility is located within the hospital's core based statistical area (CBSA)[9] and 0 otherwise. Approximately 43% of reporting hospitals had a VA facility within their CBSA.

Hypothesis 5, hospital size, is tested through a compound variable comprised of two measures: Bed size *(BSC)* and number of full-time equivalents per hospital *(FTEH)*. The hospital bed size (n=2157) is self-reported as a categorical number in the AHA annual survey. Bed size is an established measure of hospital size (Bazzoli et al., 1999). Bed size for the study population ranged from 1-8 which represent 6-500+ beds[10]. Description of the interval coding is illustrated in Table 10. Dummy variables are added to isolate the data and enhance their effect. Descriptive statistics for the measure Bed Size are illustrated in Appendix C.

The overall number of FTEs that work in the hospital is a continuous number (n=2157), and it includes part-time employees whose fractional contribution to an FTE increases the overall number (rounded to the nearest integer). Using FTEs as a

[9] CBSA is calculated annually by the U.S. Office of Management and Budget.
[10] Actual number of beds is not reported in this field. It is reported as a categorical field.

Table 10.

Bed-Size Coding Descriptions

Code	Description
1	6-24 beds
2	25-49 beds
3	50-99 beds
4	100-199 beds
5	200-299 beds
6	300-399 beds
7	400-499 beds
8	500 or more beds

measure could serve as a covariate with bed size (muticollinearity is tested later). The range of FTEs is 0 - 16,423, the mean is 1,385, and median is 875. The data are heavily skewed. The literature does not show data transformations for this variable, but due to the unusual distribution and tests of multicollinearity (discussed later), I chose to use the Log of the continuous value[11]. Descriptive statistics for FTEs are illustrated in Appendix C.

Hypothesis 6 is tested through a compound variable comprised of three measures: Status as a General Hospital (*GENHOS*, n=1973), status as a teaching hospital (*Teach*_T), and the case mix index (*@2009CMI*, n=2118). The hospital's status as a general hospital (n=1973) is a binary number self-reported in the AHA annual survey – unfortunately, there is not sufficient cell depth on the negative

[11] As explained later, the measure FTEH would not converge without this transformation.

responses to use this variable (see Appendix C). Therefore, status as a general hospital is eliminated from the model until a larger data set can be found.

The hospital's teaching status (n=2157) is collected by the AHA annual survey. The survey asks, "Is your organization a member of Council of Teaching Hospital of the Association of American Medical Colleges (COTH)?" Responses are binary in nature. An assumption is made that most teaching hospitals are members of this professional organization. Teaching status for the study population ranged from 1-2, 89.6% of which were not teaching hospitals. Descriptive statistics are illustrated in Appendix C. Data are transformed from 1-2 to 0-1; in both conditions, "1" is the desired response.

The case mix Index (n=2118), also known as the CMI, measures the organization's complexity of care. It is measured by averaging the overall Diagnostic Related Groups (DRGs) for Medicare patients. Data are provided by the CMS which adjusts the cost per patient up or down for that hospital based on whether the CMI is below or above 1.0, respectively. The resulting index shows the organization's care complexity weighted by the complexity of the industry. The indices range from 0.62 – 2.83. Descriptive statistics for the case mix index are illustrated in Appendix C.

The variable *Positive cash flow* composed of one measure, Capital expenditures (*CEAMT*). This measure (n=1738) is self-reported in the AHA annual survey. It is a continuous measure ranging from -770,297 to $ 1,469,973,663. Positive cash flow of a hospital is an established measure for a tendency to adopt new technology (Bazzoli et al., 1999; Ginn et al., 2011; Wang et al., 2005). Forty-one negative values were removed because previous literature only evaluated positive cash flow. As with FTEH, the histogram for the CEAMT data is highly unusual. The literature does not show data transformations for this variable, but due to the unusual distribution and tests of multicollinearity (discussed later), I chose to enter the measure as the Log of the continuous value[12]. Hypothesis 7 predicts that hospitals with large expenditures would have greater liquidity and less of a fiscal reason that would prevent the adoption of the EHR. The larger capital expenditures should be more highly associated with EHR adoption. Appendix C lists the descriptive statistics for this measure.

Hypothesis 8 is tested through one IV (source of influence – internal or external) and one DV (EHR adoption). A comparison of the effect size for all internal and external measures is done to test this hypothesis.

Hypothesis 9 is tested through all of the same IVs (df = 19) and one DVs (CPOE_x). Each DV is tested by itself, so the test is run five times. Computerized Provider Order Entry use is reported in the AHA-HIT supplement survey, and the sample size varies with the measure ($1640 \le n \le 1660$). The survey asks a series of questions concerning CPOE use in various areas of care (laboratory, radiology, pharmacy, consultations, nursing). Responses ranged from 1-6. Multicollinearity may be a problem with this variable. Data transformations changed this variable from ordinal to binary. Table 11 shows the data as they are reported and recoded.

[12] As explained later, the measure would not converge in the logistic regression analysis without taking the log.

Table 11.

CPOE Responses as Reported and Re-coded

AHA Code	Description	Re-code
1	Fully implemented across all units	1
2	Fully implemented in at least one unit	1
3	Beginning to implement in at least one unit	0
4	Have resources to implement in the next year	0
5	Do not have resources but considering	0
6	Not in place and not considering	0

Data Cleaning

Data are screened through descriptive statistics (Appendix C) to evaluate missing data. The study plans to use a listwise approach to eliminate all cases with missing data. Most measures possess 2157 cases of complete data with the exception of HIE participation, CMI, and Capital expenditures. Responses 1-2 are coded as 1; all others were recoded to 0. The smallest n for the study should be 1738. Each variable contains greater than 30 cases, so the strength of generalization is strong.

Because logistic regression is strongest with large sample sizes, a maximum number of cases is sought. The total number of acute-care hospitals in the US in 2009 registered with the AHA was 5733. Records with missing fields were eliminated from the study resulting in a sample size of 1640, accounting for 28.3% of the AHA population. The power ratio for this study is 1.00.

Tests of Multicollinearity

Tests of multicollinearity show mixed results (phase 1 illustrated in Appendix E), and the test results for all dependent variables (phases 1 and 2) are virtually identical.

There is no VIF greater than 10 or tolerance less than 0.1. In the multicollinearity matrix, Eigenvalues 5 and 6 are significantly smaller than the rest, but the variance proportions only show a problem in value 6. In this dimension, the CMS density and case mix index account for greater than 100% of the variance. This will reduce the overall effectiveness of the model because in some way these two variables violate the assumption of multicollinearity. However, these two variables do not demonstrate difficulties converging in the logistic regression equasions.

In phase two of the study, multicollinearity was tested for each DV. Appendix D shows the test. As illustrated in the matrix from CPOE_Lab, there are small concerns with multiple variables. None of the results are unacceptable, but these numbers will be helpful later to explain why the FTEH and CEAMT variables do not converge when the logistic regression is run. These two variables are the ones with highly unusual distributions. Examining the graphical distribution of the data indicates that there is no clear place to divide into groups, therefore I decided to take the log of both of these continuous variables so that they could be included in both phases of the study. Using the log enabled the variables to converge in the statistical test. To interpret the results, I took the anti-log of the odds ratio and coefficient.

Binary Logistic Regression Test – Phase One

A binary logistics regression analysis was performed on EHR adoption as outcome and 11 factors (df=18): HHI, MHS membership, HIE participation, ownership, CMS density, VA locally, bed size, number of FTEs, status as a teaching hospital, case mix index, and capital expenditures; including dummy variable groups and discounting reference groups, the df=19. Tables 12 illustrates the results for these variables.

Table 12.

Regression Results for the Kruse Theory (EHR adoption)

				95% C.I.for EXP(B)	
		B (S.E.)	Exp(B)	Lower	Upper
x_1	HHI	0.38 (0.28)	1.46	0.85	2.51
x_{2a}	MHSMEMB_T	0.40 (0.17)**	1.50	1.07	2.10
x_{2b}	HIE_T	0.03 (0.17)	1.03	0.74	1.44
x_{2c}	CNTRL_gov	-0.15 (0.22)	0.86	0.56	1.32
x_{2d}	CNTRL_iofp	-0.96 (0.23)***	0.39	0.25	0.60
x_3	CMS_Density	0.59 (0.62)	1.81	0.54	6.08
x_4	VA_local	0.05 (0.19)	1.05	0.72	1.53
x_{5a}	BSC_(6_24)	0.05 (0.96)	1.05	0.16	6.91
x_{5b}	BSC_(25_49)	-0.05 (0.83)	0.95	0.19	4.79
x_{5c}	BSC_(50_99)	-0.01 (0.77)	0.99	0.22	4.46
x_{5d}	BSC_(100_199)	-0.49 (0.71)	0.61	0.15	2.44
x_{5e}	BSC_(200_299)	-0.85 (0.68)	0.43	0.11	1.64
x_{5f}	BSC_(300_399)	-0.84 (0.68)	0.43	0.11	1.64
x_{5g}	BSC_(400_499)	-0.48 (0.76)	0.62	0.14	2.75
x_{5h}	Ln_FTEH	0.79 (0.22)***	2.21	1.45	3.36
x_{6b}	Teach_T	-0.04 (0.49)	0.96	0.37	2.53
x_{6c}	@2009CMI	0.05 (0.40)	1.05	0.49	2.29
x_7	Ln_CMEAT	0.15 (0.07)**	1.16	1.02	1.32
k	Constant	-5.78 (1.81)	0.00		

*p<.1, **p<.05, ***p<.001

Analysis was performed with PASW. A total of 1640 cases were used with continuous, categorical, and binary factors. The overall χ^2 (18, n=1640) = 168.89

(*p*<.001), and at most, the model accounts for only 18.2% of the variance, which tells me that the predictors in the model are only slightly different than the constant alone. However, the Hosmer and Lemeshow Test χ^2 (8, n=1640) = 13.36 (*p*>.05), which tells me that the model does have a significant effect.

Four measures were significant in phase one of the study: Ownership (independently-owned, for-profit) and the number of FTEs were highly significant (p<.001), while MHS membership, and capital expenditures were significant (*p*<.05). The odds ratios for each predictor show a range of association for adoption of the EHR. The odds of a hospitals that is part of a MHS adopting the EHR are 1.50 times a non-member. Ownership is a categorical variable, and the non-government owned not-for-profit hospital group was held as the reference. The odds of EHR adoption for the investor- owned, for profit hospital is 0.39 times that of the reference group (non-government, for-profit), thus the negative coefficient of -0.96.

The number of FTEs in a hospital and the capital expenditures were entered as continuous variables. In the case of these variables, the log of the measure was used. The anti-log was used to interpret the results. The odds ratio that resulted for the log of FTEH was 2.21, and the coefficient was 0.79. The anti-log for these numbers are 9.10 and 2.21, respectively. This means that for every one additional FTE, the odds of the HCO adopting the EHR increase by 9.10 times. Likewise, the odds ratio for the log of capital expenditures was 1.16 and the coefficient 0.15. The anti-log for these results are 3.20 and 1.16. This means that for each additional dollar expended, the odds of the HCO adopting the EHR increase by 3.20 times.

The Nagelkerke R Square illustrates that this model accounts for 18.2% of the variance for EHR adoption. The odds ratio illustrates that the factors associated with EHR adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory is:

$$P(Y) = \frac{1}{1+e^{-(-5.78+0.38X1+0.40X_{2a}+0.03X_{2b}-0.15X_{2c}-0.96X_{2d}\ldots+\,1.16X_7)}}$$

Binary Logistic Regression Test – Phase Two

A binary logistics regression analysis was performed on five varieties of CPOE adoption as outcome and 11 factors (df=183): HHI, MHS membership, HIE participation, ownership, CMS density, VA locally, bed size, number of FTEs, status as a teaching hospital, case mix index, and capital expenditures. The number of cases used depended on the DV; a range of 1646-1660 cases were used with continuous, categorical, and binary factors. Table 13 illustrates the overall χ^2, and the range of variance accounted for (13.0%-15.7%).

I analyzed the data with PASW. The overall chi-square values were all significant: e.g., CPOE_Lab χ^2 (18, n=1646) = 167.75 (p<.001). The amount of variance accounted for in the model is indicative of a moderate effect size. Table 14 illustrates the overall results for the Hosmer and Lemeshow, which tells me that the model does have a significant effect.

Table 13.

Regression Results for the Kruse Theory (CPOE Adoption)

	Residual	Overall	Negerlkerke R2	
Lab	χ^2 (18) = 160.57	χ^2 (18) = 167.75	13.00%	n=1646
Rad	χ^2 (18) = 165.83	χ^2 (18) = 173.27	13.30%	n=1660
Med	χ^2 (18) = 174.46	χ^2 (18) = 184.02	14.20%	n=1655
Cons	χ^2 (18) = 193.00	χ^2 (18) = 202.48	15.70%	n=1655
Nurs	χ^2 (18) = 161.17	χ^2 (18) = 169.41	13.00%	n=1659
all measures (p <.000)				

Table 14.

Results of the Hosmer and Lemeshow for All Five DVs

Hosmer & Lemeshow	
Lab	χ^2 (8) = 9.28, (p >.05)
Rad	χ^2 (8) = 9.30, (p >.05)
Med	χ^2 (8) = 7.76, (p >.05)
Cons	χ^2 (8) = 5.77, (p >.05)
Nurs	χ^2 (8) = 3.93, (p >.05)

Logistic regression results for CPOE_Laboratory are illustrated in Table 15. The overall χ^2 (18, n=1646) = 167.75 (p<.001), and at most, the model accounts for only 13.0% of the variance, which tells me that the predictors in the model are only slightly different than the constant alone. However, the Hosmer and Lemeshow Test χ^2 (8, n=1646) =9.28 (p>.05), which tells me that the model does have a small effect. Eight measures were significant in CPOE_Laboratory: HIE participation and status as a teaching hospital (p<.001), Bed size (6-24), the number of FTEs in the hospital and

Table 15.

Results of the Logistic Regression for CPOE Laboratory

		B (S.E.)	Exp(B)	95% C.I.for EXP(B) Lower	Upper
x_{1}	HHI	-0.36 (0.20)*	0.70	0.47	1.03
x_{2a}	MHSMEMB_T	0.10 (0.11)	1.11	0.89	1.38
x_{2b}	HIE_T	0.39 (0.11)***	1.48	1.20	1.83
x_{2c}	CNTRL_gov	0.18 (0.15)	1.20	0.90	1.60
x_{2d}	CNTRL_iofp	-0.31 (0.19)*	0.73	0.50	1.07
x_{3}	CMS_Density	-0.51 (0.47)	0.60	0.24	1.53
x_{4}	VA_local	0.08 (0.13)	1.09	0.85	1.40
x_{5a}	BSC_(6_24)	1.37 (0.63)**	3.95	1.16	13.44
x_{5b}	BSC_(25_49)	0.74 (0.44)*	2.10	0.88	5.00
x_{5c}	BSC_(50_99)	0.56 (0.37)	1.75	0.84	3.61
x_{5d}	BSC_(100_199)	0.27 (0.30)	1.31	0.72	2.36
x_{5e}	BSC_(200_299)	0.40 (0.27)	1.49	0.88	2.53
x_{5f}	BSC_(300_399)	0.29 (0.26)	1.33	0.80	2.20
x_{5g}	BSC_(400_499)	-0.13 (0.27)	0.88	0.52	1.49
x_{5h}	Ln_FTEH	0.52 (0.16)***	1.68	1.24	2.28
x_{6b}	Teach_T	0.86 (0.22)***	2.37	1.54	3.66
x_{6c}	@2009CMI	-0.68 (0.30)**	0.51	0.28	0.92
x_{7}	Ln_CMEAT	0.07 (0.05)	1.08	0.98	1.18
k	Constant	-4.24 (1.26)	0.01		

*$p<.1$, **$p<.05$, ***$p<.001$

case mix index (p<.05), Ownership (independently-owned, for-profit) and Bed size (25-49 beds, (p<.1).

The odds ratios for each predictor show a range of association for adoption of CPOE_Laboratory. For each one unit increase in HHI, the odds of CPOE_laboratory adoption increases by 0.70 times. The odds of an HCO that participates in an HIE adopting CPOE_Radiology are 1.48 times an HCO that does not participate.

Ownership is a categorical variable, and the non-government owned, not-for-profit hospital group was held as the reference. The odds of CPOE_Laboratory adoption for the investor-owned for profit hospital is 0.73 times that of the reference group, thus the negative coefficient of -0.31.

Bed size is a categorical variable, the group with the highest number of beds (500+) was used as the reference group. The odds of CPOE_Laboratory adoption for HCOs with 6-24 beds are 3.95 times that of the reference group. The odds of CPOE_Laboratory adoption for HCOs with 25-49 beds are 2.10 times that of the reference group.

The number of FTEs in a hospital was entered as a continuous variable. The transformation chosen was the log of the measure. The anti-log of the odds ratio and coefficient is necessary to properly interpret the results. The odds ratio that resulted for the log of FTEH was 1.68, and the coefficient was 0.52. The anti-log for these numbers are 5.37 and 1.68, respectively. This means that for every one additional FTE, the odds of adopting CPOE_Laboratory increases by 5.37 times.

The odds of an HCO with a teaching status adopting CPOE_Laboratory are 2.37 times one without a teaching status. For each one unit increase in the case mix index, the odds of an HCO adopting CPOE_Laboratory decrease by 0.51 times.

The Nagelkerke R Square illustrates that this model accounts for 13.0% of the variance for CPOE_Laboratory adoption. The Odds Ratio illustrates that the factors associated with CPOE_Laboratory adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory for CPOE_Lab is:

$$P(Y) = \frac{1}{1+e^{-(-4.67-0.36X1+0.10X_{2a}+0.39X_{2b}+0.18X_{2c}-0.31X_{2d}\ldots-3.24X_7)}}$$

Table 16 illustrates the results of CPOE_Radiology. Variables that were significant were HIE participation and status as a teaching hospital (p<.001), Bed size (6-24), the number of FTEs in the hospital and case mix index (*p*<.05), Ownership (independently-owned, for-profit) and Bed size (25-49 beds, (*p*<.1).

For each one unit increase in the HHI, the odds of an HCO adopting CPOE_Radiology decrease by 0.70. The odds of an HCO that participates in an HIE adopting the CPOE_Radiology are 1.50 times that of an HCO that does not participate.

Ownership is a categorical variable, and the non-government owned, not-for-profit hospital group was held as the reference. The odds of CPOE_Radiology adoption for the investor-owned for profit hospital is 0.70 times that of the reference group, thus the negative coefficient of -0.36.

Table 16.

Results of the Logistic Regression for CPOE Radiology

				95% C.I.for EXP(B)	
		B (S.E.)	Exp(B)	Lower	Upper
x_{1}	HHI	-0.35 (0.20)*	0.70	0.48	1.03
x_{2a}	MHSMEMB_T	0.16 (0.11)	1.17	0.94	1.46
x_{2b}	HIE_T	0.40 (0.11)***	1.50	1.21	1.85
x_{2c}	CNTRL_gov	0.22 (0.15)	1.24	0.94	1.65
x_{2d}	CNTRL_iofp	-0.36 (0.19)*	0.70	0.48	1.02
x_{3}	CMS_Density	-0.60 (0.47)	0.55	0.22	1.39
x_{4}	VA_local	0.10 (0.13)	1.11	0.86	1.42
x_{5a}	BSC_(6_24)	1.12 (0.63)*	3.07	0.88	10.63
x_{5b}	BSC_(25_49)	0.73 (0.44)*	2.08	0.88	4.95
x_{5c}	BSC_(50_99)	0.59 (0.37)	1.81	0.88	3.74
x_{5d}	BSC_(100_199)	0.32 (0.30)	1.37	0.76	2.47
x_{5e}	BSC_(200_299)	0.38 (0.27)	1.46	0.86	2.47
x_{5f}	BSC_(300_399)	0.27 (0.26)	1.31	0.79	2.16
x_{5g}	BSC_(400_499)	-0.19 (0.27)	0.83	0.49	1.40
x_{5h}	Ln_FTEH	0.52 (0.16)***	1.67	1.24	2.27
x_{6b}	Teach_T	0.86 (0.22)***	2.37	1.54	3.64
x_{6c}	@2009CMI	-0.64 (0.30)**	0.53	0.29	0.95
x_{7}	Ln_CMEAT	0.07 (0.05)	1.07	0.98	1.18
k	Constant	-4.24 (1.26)	0.01		

$^{*}p<.1$, $^{**}p<.05$, $^{***}p<.001$

Bed size is a categorical variable, the group with the highest number of beds (500+) was used as the reference group. The odds of CPOE_Radiology adoption for HCOs with 6-24 beds are 3.07 times that of the reference group. The odds of CPOE_Radiology adoption for HCOs with 25-49 beds are 2.08 times that of the reference group.

The number of FTEs in a hospital was entered as a continuous variable. The transformation chosen was the log of the measure. The anti-log of the odds ratio and coefficient is necessary to properly interpret the results. The odds ratio that resulted for the log of FTEH was 1.67, and the coefficient was 0.52. The anti-log for these numbers are 5.33 and 1.67, respectively. This means that for each one additional FTEs in a hospital, the odds of adopting CPOE_Radiology increases by 5.33 times.

The odds of an HCO with a teaching status adopting CPOE_Radiology are 2.37 times one without a teaching status. For each one unit increase in the case mix index, the odds of an HCO adopting an CPOE_Radiology decrease by 0.53 times.

The Nagelkerke R Square illustrates that this model accounts for 13.3% of the variance for CPOE_Radiology adoption. The Odds Ratio illustrates that the factors associated with CPOE_Radiology adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory for CPOE_Rad is:

$$P(Y) = \frac{1}{1+e^{-(-4.24-0.35X1+0.16X_{2a}+0.40X_{2b}+0.22X_{2c}-.36X_{2d}\ldots-1.09X_{7})}}$$

Table 17 illustrates the logistic regression results for CPOE_Medication. The variables that were significant were HIE participation and status as a teaching hospital (*p*<.001). CMS density, Bed size (50-99), the number of FTEs in the hospital and case mix index (*p*<.05), Ownership (independently-owned, for-profit), Bed size (25-49) and Bed size (200-299) and capital expenditures, (*p*<.1).

Table 17.

Results of the Logistic Regression for CPOE Medication

				95% C.I.for EXP(B)	
		B (S.E.)	Exp(B)	Lower	Upper
x_1	HHI	-0.23 (0.20)	0.79	0.54	1.18
x_{2a}	MHSMEMB_T	0.13 (0.13)	1.14	0.91	1.42
x_{2b}	HIE_T	0.46 (0.11)***	1.58	1.28	1.96
x_{2c}	CNTRL_gov	0.15 (0.15)	1.16	0.87	1.54
x_{2d}	CNTRL_iofp	-0.37 (0.20)*	0.69	0.47	1.02
x_3	CMS_Density	-1.13 (0.48)**	0.32	0.13	0.83
x_4	VA_local	0.17 (0.13)	1.19	0.92	1.53
x_{5a}	BSC_(6_24)	0.97 (0.66)	2.65	0.72	9.69
x_{5b}	BSC_(25_49)	0.77 (0.45)*	2.17	0.90	5.26
x_{5c}	BSC_(50_99)	0.74 (0.38)**	2.10	1.01	4.39
x_{5d}	BSC_(100_199)	0.39 (0.30)	1.48	0.82	2.69
x_{5e}	BSC_(200_299)	0.44 (0.27)*	1.56	0.92	2.65
x_{5f}	BSC_(300_399)	0.30 (0.26)	1.35	0.82	2.23
x_{5g}	BSC_(400_499)	-0.11 (0.27)	0.90	0.53	1.52
x_{5h}	Ln_FTEH	0.53 (0.16)***	1.70	1.24	2.31
x_{6b}	Teach_T	0.88 (0.22)***	2.41	1.57	3.69
x_{6c}	@2009CMI	-0.83 (0.31)**	0.44	0.24	0.79
x_7	Ln_CMEAT	0.09 (0.05)*	1.09	0.99	1.21
k	Constant	-4.25 (1.27)	0.01		

**p*<.1, ***p*<.05, ****p*<.001

The odds of an HCO that participates in an HIE adopting CPOE_Medication are 1.58 times that of an HCO that does not participate. Ownership is a categorical variable, and the non-government owned, not-for-profit hospital group was held as the reference. The odds of CPOE_Medication adoption for the investor-owned for profit hospital are 0.69 times that of the reference group, thus the negative coefficient of -0.37. For each one unit increase in CMS density, the odds of CPOE_Medication adoption decrease by 0.32 times.

Bed size is a categorical measure, the group with the highest number of beds (500+) was used as the reference group. The odds of CPOE_Medication adoption for HCOs with 25-49 beds are 2.65 times that of the reference group. The odds of CPOE_Medication adoption for HCOs with 50-99 beds are 2.10 times that of the reference group. The odds of CPOE_Medication adoption for HCOs with 200-299 beds are 1.56 times that of the reference group.

The number of FTEs in a hospital in the hospital were entered as continuous measure. The transformation chosen was the log of the measure. The anti-log of the odds ratio and coefficient is necessary to properly interpret the results. The odds ratio that resulted for the log of FTEH was 1.70, and the coefficient was 0.53. The anti-log for these numbers is 5.45 and 1.70, respectively. This means that for every one additional FTE, the odds of adopting CPOE_Medication increases by 5.45 times.

The odds of an HCO with a teaching status adopting CPOE_Medication are 2.41 times one without a teaching status. For each one unit increase in the case mix index, the odds of an HCO adopting an CPOE_Medication decrease by 0.44 times. Capital expenditures was entered as a continuous measure. The results for the log of capital expenditures showed an odds ratio of 1.09 and a coefficient of 0.09. The anti-log of these numbers is 2.98 and 1.09, respectively. This means that for each additional dollar spent, the odds of adopting CPOE_Medication increase by 12.3 times.

The Nagelkerke R Square illustrates that this model accounts for 14.2% of the variance for CPOE_Medication adoption. The Odds Ratio illustrates that the factors associated with CPOE_Medication adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory for CPOE_Med is:

$$P(Y) = \frac{1}{1+e^{-(-4.25-0.23X1+0.13X_{2a}+0.46X_{2b}+0.15X_{2c}-0.37X_{2d}\ldots-1.09X_7)}}$$

Table 18 illustrates the results for CPOE_Consultations. The variables that were significant were HIE participation and status as a teaching hospital (p<.001), Ownership (independently-owned, for-profit), the number of FTEs in the hospital, and case mix index (p<.05), CMS density, VA local, and Bed size (50-99) (p<.1).

The odds of an HCO that participates in an HIE adopting CPOE_Consultations are 1.58 times that of an HCO that does not participate. Ownership is a categorical variable, and the non-government owned, not-for-profit hospital group was held as the reference. The odds of CPOE_Consultations adoption for the investor-owned for profit hospital are 0.51 times that of the reference group, thus the negative coefficient of -0.68. For each one unit increase in CMS density, the odds of CPOE_Consultations adoption decrease by 0.43 times. The odds of a hospital with a VA hospital within the same CBSA adopting CPOE_Consultations is 1.24 times that of an HCO without a VA hospital within the same CBSA.

Table 18.

Results of the Logistic Regression for CPOE Consultations

		B (S.E.)	Exp(B)	95% C.I.for EXP(B)	
				Lower	Upper
x_1	HHI	-0.23 (0.21)	0.80	0.53	1.20
x_{2a}	MHSMEMB_T	0.13 (0.12)	1.14	0.90	1.43
x_{2b}	HIE_T	0.46 (0.11)***	1.58	1.27	1.97
x_{2c}	CNTRL_gov	0.14 (0.15)	1.15	0.86	1.55
x_{2d}	CNTRL_iofp	-0.68 (0.22)**	0.51	0.33	0.78
x_3	CMS_Density	-0.85 (0.50)*	0.43	0.16	1.13
x_4	VA_local	0.22 (0.13)*	1.24	0.96	1.61
x_{5a}	BSC_(6_24)	0.82 (0.70)	2.27	0.58	8.90
x_{5b}	BSC_(25_49)	0.46 (0.47)	1.59	0.64	3.95
x_{5c}	BSC_(50_99)	0.65 (0.38)*	1.91	0.90	4.03
x_{5d}	BSC_(100_199)	0.39 (0.31)	1.48	0.81	2.69
x_{5e}	BSC_(200_299)	0.32 (0.27)	1.37	0.80	2.34
x_{5f}	BSC_(300_399)	0.24 (0.26)	1.27	0.77	2.10
x_{5g}	BSC_(400_499)	-0.06 (0.27)	0.94	0.56	1.60
x_{5h}	Ln_FTEH	0.56 (0.16)***	1.75	1.27	2.40
x_{6b}	Teach_T	0.76 (0.22)***	2.14	1.40	3.26
x_{6c}	@2009CMI	-0.63 (0.32)**	0.53	0.29	0.99
x_7	Ln_CMEAT	0.05 (0.05)	1.06	0.96	1.17
k	Constant	-4.42 (1.31)	0.01		

* p<.1, ** p<.05, *** p<.001

Bed size is a categorical variable, the group with the highest number of beds (500+) was used as the reference group. The odds of CPOE_Consultations adoption for HCOs with 50-99 beds are 1.91 times that of the reference group.

The number of FTEs in a hospital was entered as a continuous variable. The transformation chosen was the log of the measure. The anti-log of the odds ratio and coefficient is necessary to properly interpret the results. The odds ratio that resulted for the log of FTEH was 1.75, and the coefficient was 0.56. The anti-log for these numbers are 5.73 and 1.75, respectively. This means that for each one additional FTEs in a hospital, the odds of adopting CPOE_Consultations increases by 5.73 times.

The odds of an HCO with a teaching status adopting CPOE_Consultations are 2.14 times one without a teaching status. For each one unit increase in the case mix index, the odds of an HCO adopting an CPOE_Consultations decrease by 0.53 times.

The Nagelkerke R Square illustrates that this model accounts for 15.7% of the variance for CPOE_Consultations adoption. The Odds Ratio illustrates that the factors associated with CPOE_Consultations adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory for CPOE_Consult is:

$$P(Y) = \frac{1}{1+e^{-(-4.42-0.23X1+0.13X_{2a}+0.46X_{2b}+0.14X_{2c}-0.68X_{2d}\ldots+1.06X_7)}}$$

Table 19 illustrates the results from the logistic regression analysis for CPOE_Nursing. The variables that were significant were HIE participation, number of FTEs, and teaching status (p<.001). Ownership (independently-owned, for-profit), Bed size (50-99), status as a teaching hospital, and case mix index (*p*<.05), Bed size (6-24), Bed size (100-199), and Bed size (200-299, *p*<.1).

Table 19.

Results of the Logistic Regression for CPOE Nursing

		B (S.E.)	Exp(B)	95% C.I.for EXP(B) Lower	Upper
x_1	HHI	-0.22 (0.20)	0.81	0.55	1.18
x_{2a}	MHSMEMB_T	0.02 (0.11)	1.02	0.82	1.27
x_{2b}	HIE_T	0.36 (0.11)***	1.44	1.17	1.78
x_{2c}	CNTRL_gov	0.09 (0.15)	1.10	0.83	1.46
x_{2d}	CNTRL_iofp	-0.40 (0.19)**	0.67	0.46	0.98
x_3	CMS_Density	-0.66 (0.48)	0.52	0.21	1.32
x_4	VA_local	0.06 (0.13)	1.06	0.82	1.36
x_{5a}	BSC_(6_24)	1.09 (0.65)*	2.98	0.83	10.72
x_{5b}	BSC_(25_49)	0.83 (0.44)*	2.29	0.97	5.45
x_{5c}	BSC_(50_99)	0.88 (0.37)**	2.40	1.16	4.95
x_{5d}	BSC_(100_199)	0.50 (0.30)*	1.65	0.91	2.97
x_{5e}	BSC_(200_299)	0.44 (0.27)*	1.56	0.92	2.63
x_{5f}	BSC_(300_399)	0.33 (0.26)	1.39	0.85	2.30
x_{5g}	BSC_(400_499)	-0.18 (0.27)	0.83	0.49	1.41
x_{5h}	Ln_FTEH	0.63 (0.16)***	1.87	1.38	2.53
	(back transformec	1.87	6.48		
x_{6b}	Teach_T	0.76 (0.22)***	2.14	1.39	3.28
x_{6c}	@2009CMI	-0.61 (0.30)*	0.54	0.30	0.98
x_7	Ln_CMEAT	0.07 (0.05)	1.07	0.98	1.18
	(back transformec	1.07	2.92		
k	Constant	-4.94 (1.26)	0.01		

*p<.1, **p<.05, ***p<.001

The odds of an HCO that participates in an HIE adopting CPOE_Nursing are 1.44 times that of an HCO that does not participate. Ownership is a categorical variable, and the non-government owned, not-for-profit hospital group was held as the reference. The odds of CPOE_Nursing adoption for the investor-owned for profit hospital are 0.67 times that of the reference group, thus the negative coefficient of -0.40.

Bed size is a categorical variable, the group with the highest number of beds (500+) was used as the reference group. The odds of CPOE_Nursing adoption for HCOs with 6-24 beds, 25-49, 50-99, 100-199, and 200-299 are 2.98, 2.29, 2.40, 1.65, and 1.56 times that of the reference group, respectively.

The number of FTEs in a hospital was entered as a continuous variable. The transformation chosen was the log of the measure. The anti-log of the odds ratio and coefficient is necessary to properly interpret the results. The odds ratio that resulted for the log of FTEH was 1.87, and the coefficient was 0.63. The anti-log for these numbers is 6.48 and 1.87, respectively. This means that for each one additional FTEs in a hospital, the odds of adopting CPOE_Consultations increases by 6.48 times. The odds of an HCO with a teaching status adopting CPOE_Nursing are 2.14 times one without a teaching status. For each one unit increase in the case mix index, the odds of an HCO adopting an CPOE_Nursing decrease by 0.54 times.

The Nagelkerke R Square illustrates that this model accounts for 13.1% of the variance for CPOE_Nursing adoption. The Odds Ratio illustrates that the factors associated with CPOE_Nursing adoption vary in comparison to the reference group or the constant alone.

The resulting equation for the Kruse Theory for CPOE_Nursing is:

$$P(Y) = \frac{1}{1+e^{-(-4.94-0.22X1+0.02X_{2a}+0.36X_{2b}+0.09X_{2c}-0.40X_{2d}\cdots+1.07X_{7})}}$$

External Versus Internal Factors

When I ran logistics regression equations separately for external versus internal variables, I received mixed results. The χ^2 values for external residual, overall, and Hosmer and Lemeshow are significant to the same levels. The differences between the residual and overall for external was greater than that of internal, but the internal factors accounted for a greater percentage of variance (16.2% versus 9.3%). The significance for individual factors was greater for external factors than for internal. All external factors (df=7) were significant (p<.05), while only two internal factors (df = 12) were significant (p<.1). Therefore, the external factors were more highly associated with the adoption of the EHR and CPOE.

Hypothesis Testing

Hypothesis 1 predicted that those HCOs in more competitive environments will be more likely to adopt the EHR. Results from this study do show with strong statistical significance that the HHI is associated with EHR adoption. Referring back to the conceptual model (Figure 4), competitiveness in healthcare has consistently been measured with the HHI (Pfeffer and Salancik, 1978 & 2003; Wang et al., 2005; Ginn et al., 2011). The H_a is accepted and H_o is rejected for hypothesis 1: HCOs in competitive environments are more likely to adopt the EHR, but not CPOE_x. The HHI measure did not demonstrate a statistically significant effect on the adoption of any variety of CPOE examined.

Hypothesis 2 postulated that HCOs that participate in strategic alliances will be more likely to adopt the EHR. Three measures were identified, and two of the three were statistically significant between both phases of the study. The strong association between HIE participation and CPOE_x adoption was a surprise, and it is not previously addressed in the literature. However, HIE Participation logically follows the incentives for Meaningful Use, and there should be a high correlation between HIE participation and CPOE_x adoption. It is surprising that there was no statistical significance with this measure in Phase I of the study. System affiliation and ownership are strongly supported in the literature (Bazzoli et al., 2000; Pfeffer and Salancik, 1978 & 2003; Rogers; 1995 & 2003; DesRoches et al., 2010; Ginn et al., 2005; Wang et al., 2005; Wolf et al., 201), and the significance of these measures should also not be a surprise. Across both phases of the study, Ownership (investor-owned, for-profit HCOs) was statistically significant, in comparison to the reference group. The variable, MHS membership, did not show a statistically significant effect on the adoption of CPOE_x, and HIE participation did not show a statistically significant effect on adoption of the EHR. The H_a is accepted and H_o is rejected: System affiliation is a factor associated with the adoption of the EHR and CPOE_x.

Hypothesis 3 postulated that HCOs that service populations covered by the CMS would be more likely to adopt the EHR. This variable was calculated by CMS bed days divided by total bed days. The data were continuous. Referring back to the conceptual model, this measure was chosen because Wang et al., (2005) emphasized the importance of financial factors in organizational decisions. Although the results of CMS_Density in the Kruse Theory were not significant for EHR adoption, they were significant for adoption of CPOE_Med ($p<.05$) an CPOE_Consultations ($p<.1$). The use of buyers as an external source of influence is well established in the literature (Ginn et al., 2011; Wolf et al., 2012; Rogers 1995 & 2003; Wang et al., 2005), and the CMS reports that it accounts for up to 55% of health care expenditures (2009). Because of its importance, CMS density should not be expelled from the Kruse Theory for either phase. For hypothesis 3, H_a is accepted and H_o is rejected. Further analysis should be conducted in the future to determine the reason for the small effect that CMS density had on EHR adoption.

Hypothesis 4 postulated that HCOs that compete with a VA facility will be more likely to adopt the EHR. This factor did not present a statistically significance effect for adoption of the EHR, but it did show significant association with CPOE_Consultations ($p<.1$). This result could be indicative of referrals or specialty consultations occurring between the public and private sectors. Referring back to the conceptual model, this hypothesis is supported in the literature (Bazzoli et al., 2000). For hypothesis 4, H_a is accepted and H_o is rejected: HCOs that compete with a VA facility are not more likely to adopt the EHR, but are more likely to adopt at least one dimension of CPOE_x.

Because of its presence in the literature, this measure should be reassessed in future studies.

Hypothesis 5 postulated that HCO size will be positively associated with EHR adoption. Two measures were identified for this variable, and both showed significance across the study[13]. The AHA data for bed size (BSC) was a categorical variable with 8 categories. Dummy variables were introduced to enhance group effect. The highest category was held as the reference because it represented the largest hospitals. The other measure in this variable, (FTEH), was also a continuous variable. The bed size measure seemed to be eclipsed by the strong interaction effect with the FTEH measure. Bed size showed a statistically significant effect across all groups for the adoption of CPOE_x, but not with the EHR. The two largest categories did not show significant correlation in any of the dimensions of CPOE. Bed size is a well established measure of hospital size, and it is used in other studies as a factor associated with technology adoption (Bazzoli et al., 2000; DesRoches et al., 2010; Ginn et al., 2011; Wolf et al., 2012; Wang et al., 2005). The number of FTEs in the hospital showed significance across both phases of the study in all dimensions of CPOE. The violation of the assumption of multicollinearity in both phases caused concern. In both phases, the log of FTEH converged so that it could be used. Because the use of these variables is frequent in the literature, both are left in the Kruse Theory. For hypothesis 5, H_a is accepted and H_0 is rejected. The size of the hospital has a positive effect on the

[13] FTEH was eliminated in phase one because it violated the assumption of multicollinearity and it would not converge into the logistic regression.

adoption of the EHR and CPOE_x. Future analysis should be conducted to identify and minimize the interaction effect between these measures and others used in the Kruse Theory.

Hypothesis 6 postulated that HCOs that coordinate complex care will be more likely to adopt the EHR. Three measures were selected from the conceptual model: status as a general hospital, status as a teaching hospital, and the case mix index as reported by the CMS (2009). Status as a general hospital did not demonstrate statistical association with the EHR or CPOE_x. Status as a teaching hospital demonstrated a highly significant effect for the adoption of CPOE_x, but no significant effect for the adoption of the EHR. Case mix index showed strongly significant effects on the adoption of CPOE_x ($p<.05$), but not the EHR. Referring to the conceptual model, teaching status is firmly established as a strong association with EHR adoption (DesRoches et al., 2010; Farley & Hogan, 1990; Wang et al., 2005). Also, the CMI is an established measure for adoption of innovation (Farley & Hogan, 1990). For hypothesis 5, H_a is accepted and H_o is rejected. Hospitals that coordinate more complex care are more likely to adopt the EHR and all varieties of CPOE_x studied.

Hypothesis 7 postulated that HCOs with positive cash flow will be more likely to adopt the EHR. The capital expenditures variable violated the assumption of multicollinearity for both phases of the study, but taking the log of the measure allowed it to converge in both phases of the study. This measure showed statistical association with adoption of the EHR ($p<.05$) and adoption of CPOE_Medication ($p<.1$), but not for any of the other dimensions of CPOE. Referring back to the conceptual model, the use of capital expenditures is well established in the evaluation of strategy and adoption of innovation (DesRoches et al., 2010; Ginn et al., 2011). For this reason, I decided to accept the H_a and reject the H_o. Hospitals with high capital expenditures are more likely to adopt the EHR and CPOE_x.

Hypothesis 8 postulated that external sources of influence, more than internal sources, will influence HCOs to adopt the EHR. In the full model for EHR or CPOE_x adoption, the external measures show strong association in one of the five measures ($p<.001$) and good association in two others ($p<.05$), while internal sources of influence show good association with three measures ($p<.05$). Another interesting observation is that both internal and external influences showed similar effects on CPOE_x adoption, but the measurements that showed significance changed. For hypothesis 8, H_a is accepted and H_o is rejected: External environmental factors have a greater association with EHR and CPOE_x adoption.

Hypothesis 9 was explored in the second phase of the study. It postulated that HCOs that adopt the EHR will also adopt a critical component, CPOE. Five varieties of CPOE were evaluated: Laboratory, radiology, medicine, consultations, and nursing orders. As discussed throughout this chapter, three of the factors associated with adoption of the EHR also associated with the adoption of all varieties of CPOE_x. This should not be much of a surprise. Literature as far back as 2001 by the IOM has promoted the use of CPOE as a bridge to overcome human error in medicine. For hypothesis 9, H_a is accepted and H_o is rejected.

Summary

The Kruse Theory explains associations between external environmental influences and internal organizational influences on the adoption of the EHR. The logistics regression process showed significance on four measures. The strongest associations were found between external influences and EHR adoption. The second phase of the study concludes that the same factors have a strong association with the adoption of all five varieties of CPOE studied: Laboratory, radiology, medicine, consultations, and nursing orders.

CHAPTER 7: Summary, Discussion, and Conclusion

Summary of Major Findings

Although not all variables showed significance in their association with EHR adoption or CPOE adoption, use of the variables in the Kruse Theory is justified through literature. In the first phase of the study, the variables in the Kruse Theory that demonstrated highest to lowest effects of significance are: Ownership (status as an investor-owned, for profit HCO) and number of FTEs (p<.001), MHS membership, and capital expenditures (p<.05). In the second phase of the study, the variables that demonstrated highest to lowest effects of significance are: HIE participation and status as a teaching HCO (p<.001); HHI, Ownership (status as an investor-owned, for-profit HCO), CMS density, bed size (6-24 beds), number of FTEs and case mix index (p<.05), bed size (6-24 beds, p<.1); in CPOE_Consultations only, VA local, and in CPOE_Medication only capital expenditures (p<.1). External environmental influences demonstrated stronger effect based on the 2009 data from the AHA and the CMS.

Discussion: Implications of the Findings

As deadlines for the Meaningful Use criteria continue to evolve, it becomes critical that hospital administrators take as few as steps necessary to adopt the EHR. The presence of a complex model for associating factors of adoption of the EHR and CPOE_x helps the administrator become acutely aware of the full effects of both external and internal influence. This study used data from 2009 because the HITECH Act was passed that year. This study can serve as a baseline for future studies.

The Kruse Theory can be used by hospital administrators and policy makers to illustrate the factors of influence that are associated with the adoption of the EHR and CPOE_x. As shown by the results, external influences are more strongly associated with EHR and CPOE_x adoption, and some of the internal influences, such as bed size, are not easily changed. Although hospital administrators are placed under great pressure to adopt the EHR, on many levels this study shows that the factors most s associated with its adoption are external, and are therefore largely outside the sphere of influence for the administrator. The policy maker should take the lead on inspiring and incentivizing EHR adoption through multiple channels.

The results of my study show several external factors that are highly associated with adoption of the EHR: HHI (-), ownership (+) and CMS density (+). The HHI did not show significant results in association with adoption of the EHR, but it did show a negative association with the adoption of CPOE_Laboratory and CPOE_Radiology. The industries of laboratory and radiology have developed highly independent systems: The laboratory information system (LIS) for the laboratory and the picture archival and retrieval system (PACS) for the radiology functions service those special niches, and often an interface between the LIS and PACS to the EHR becomes an additional development cost during EHR implementation. In highly competitive markets, many hospitals contract out the laboratory and radiology functions and repurpose the space within the facility for clinical activities. This avoids the additional development cost and enables a specialty lab/rad service provider provide high-quality services. In order to incentivize the adoption of CPOE_Laboratory and CPOE_Radiology, the CMS should emphasize standards of interoperability between the developers of LIS and PACS to the the industry that develops the EHR.

It was no surprise that the investor-owned, for profit HCOs were highly associated with the adoption of both the EHR and CPOE_x (in comparison with the reference group). The CMS should encourage the growth of the investor-owned, for profit HCOs and recognize that hese organizations, along with state-owned HCOs are behind the not-for-profit hospitals in the adoption of the EHR. The better capitalized organizations are leading the industry in the adoption of both the EHR and CPOE_x. The CMS should continue to incentivize and subsidize the growth of infrastructure, which will enable the investor-owned, for profit and state hospitals to tie into a high-speed backbone which would enable them to take full advantage of EHR interoperability.

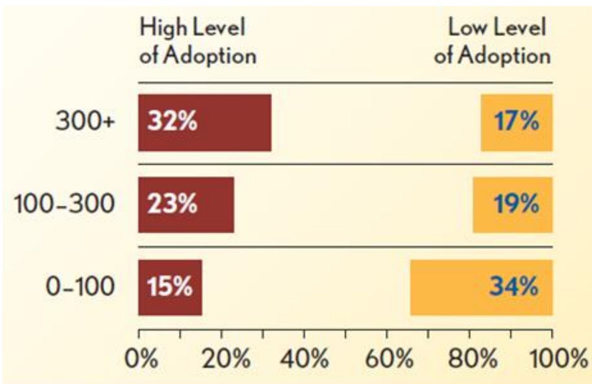
The HITECH Act is intended to serve as a needed lever to encourage EHR adoption. The CMS provides incentives for EHR adoption, and CPOE often comes as a standard module in the EHR packages. The external influence of incentives from the CMS seems to be appropriate and effective. In all likelihood, the market would have moved the healthcare industry to the EHR eventually, but the Meaningful Use incentives serve as a catalyst to this trend. The results of this study show that the CMS should take advantage of incentives used as levers to spur on the adoption of the EHR.

The association between bed size and CPOE_x adoption was surprising because previous literature shows a positive association between bed size and EHR adoption. After some research, I found three possible explanations.

I grouped the partially and fully adopted populations into one group, "adopted," which may have masked some of the distinctions found in other studies. Jha et al. (2005), Ginn, Shen, and Mosely (2011) evaluated EHR adoption at both the partial and fully-adopted levels. My results could logically vary from theirs.

The second reason my findings can differ from other research can be found in a report from the Vermont Healthcare Financial Management Association (2006). The researchers stratified bed size into several categories, as illustrated in Figure 8.

Figure 8. Level of Adoption by Bed Size



Source: Healthcare Financial Management Association (2006).

As noted, the lowest stratum, which would encompass the lowest two groups in the AHA data, shows about 50% adoption between the high and low levels of adoption. This would explain why the lower groups in the AHA database, which represent the lower bed sizes, demonstrate a higher association of EHR adoption.

The third reason my results could have differed can be explained by Ginn and Shen's (2006) presentation at the HIMSS annual conference. They explained their unusual results for bed size and EHR adoption. They suggested that the mid size to larger size bed sizes could have inefficient collections policies. This inefficiency could explain a reduced state of liquidity, which would decrease available funding for CPOE_x solutions.

Although not easily tested with the continuous versus categorical variables, there is most likely a high level of correlation between the number of FTEs, the bed size, and the capital expenditures. The test of multicollinearity for FTEH and CMEAT showed a slight problem, but had the categorical variable of bed size been in a continuous format, the three most likely would have violated this important assumption for binary logistic regression.

Referring back to the research questions posed by this study, there are many factors of influence associated with the adoption of both the EHR and CPOE_x. The particular measures used in the Kruse Theory should be analyzed further to identify the negative interaction effects between the variables. Their use in the literature is firmly established, but their use in combination showed conflict.

Limitations and Future Studies

Several limitations to this study exist. This study uses a cross-sectional design which is limited in that it does not allow for inferences of causation. It is also the weakest design for validity. However, because this study is limited to associations, the effect of this limitation is minimal. This study uses data from 2009, which is the same year that the HITECH Act was passed. It is highly unlikely that significant progress was made in the months after the legislation passed. Because this study establishes baseline data, there were low expectations for wide adoption. This study should be repeated with subsequent years' data and results compared. Not only would such a study show stronger associations, but also such a time study would show progress in specific predictors, and this quasi-experimental design would provide stronger validity. The AHA survey is also self-reported data from leaders in the HCOs, and the data were not independently verified. However, since the details of the annual survey seldom change and the HIT supplement survey was also distributed previously, hospitals are familiar with the survey instruments. This familiarity may overcome many of the errors that would be introduced by a survey with which an HCO would be unfamiliar. Finally, two variables had difficulty converging in the logistic regression equations. The log of the variables was used to enable them to converge. A more thorough examination should be conducted on these two variables to determine where the collinearity occurs, and alternate variables identified to replace them.

Future studies should look carefully at the HHI to determine effective and statistically sound means of data smoothing and other transformations to evaluate its effect on the adoption of CPOE_x. A different year should be examined and compared with that of 2009 to identify anomalies. Another possibility to measure competitiveness is to identify another measure for evaluation with its adoption of CPOE_x.

The variables, MHS membership and ownership, should be included in future studies because of their strength in the literature. MHS membership should be identified through a different measure or a different year of data used to see if there is any increase in its effect on the adoption of CPOE_x.

Dependence on the CMS as a customer is a good choice of variable, and this was demonstrated by its effect on the adoption of CPOE_x. Using CMS density should have strong association with EHR adoption. Future studies should evaluate this measure closely and see if any transformations will reveal a statistically significant effect.

Several measures should be studied further. The proximity to a VA facility should be included in future studies because of its strength in the literature (Bazzoli et al., 2000). Teaching status is firmly established as a strong association with EHR adoption (DesRoches et al., 2010; Farley & Hogan, 1990; Wang et al., 2005). Positive cash flow is also well supported by the literature (DesRoches et al., 2010; Ginn et al., 2011; Rogers, 1995 & 2003; Wang et al., 2005). Referring to the conceptual model, they should be included in the Kruse Theory. However, data transformations should be explored to see if these measures will reveal any statistically significant effect on EHR adoption.

In addition to CPOE, there are other significant components of the EHR such as CDSS. A CDSS adoption is also reported in the AHA EHR Supplement. This sub component should be explored in the same manner as CPOE_x.

Conclusions

Presidential Order in 2004 launched the national initiative for EHRs, but the lack of incentives from either the market or the government resulted in an extraordinarily slow adoption rate. This study identifies and evaluates the effects of external environmental internal organizational factors on healthcare organizations to adopt the EHR. Nine hypotheses (19 measures) are examined to associate influential factors with EHR adoption. Secondary data are analyzed and logistic regression used to quantify the relationship between the variables. Eight hypotheses are significant (p <.1) between the two phases. This study used data from 2009 because the HITECH Act was passed that year. This study can serve as a baseline for future studies. It fills a gap in the literature concerning factors associated with the adoption of the EHR and CPOE. The Kruse Theory developed is strongly based in literature and reflects complexity commensurate with the health care industry. Subsequent studies should repeat and update this model.

Bibliography

American Hospital Association. (2013). AHA Healthcare Data Viewer. Retrieved on February 18, 2013 from http://www.ahadataviewer.com/Global/Estimation%20with%20Logo.docx

Ash, J., & Bates, D. (2005). Factors and forces affecting EHR system adoption: Report of a 2004 ACMI discussion. Journal of the American Medical Informatics Association, 12(1), 8-12. doi: 10.1197/jamia.M1684

Bazzoli, G. J.; LoSasso, A.; Arnould, R.; Shalowitz, M. (2002). Hospital Reorganization and Restructuring Achieved Through Merger. Health Care Management Review. 27(1):7-20, January 2002.

Bazzoli, G. J., Chan, B., Shortell, S., & D'Aunno, T. (2000). The financial performance of hospitals belonging to health networks and systems. Inquiry 37, (3), 234-252.

Bazzoli, G. J., Shortell, S. M., Dubs, N., Chan, C., & Kralovec, P. (1999). A taxonomy of health networks and systems: Bringing order out of chaos. Health Services Research, 33(6), 1683-1717.

Blavin, F. E., Buntin, M. J. B., & Friedman, C. P. (2010). Alternative measures of electronic health record adoption among hospitals. The American Journal of Managed Care, 16(12), e293-e301.

Castillo, V., Martinez-Garcia, A. & Pulido, J. (2010). A knowledge-based taxonomy of critical factors for adopting electronic health record systems by physicians: A systematic literature review. (2010). BMC Medical Informatics and Decision Making, 10(1), 60.

Chaiken, B. (2001). Enhancing patient safety with clinically intelligent physician order entry. (2001). Nursing Economic$, 19(3), 119.

Chau, P., and Tam, K. ''Organizational Adoption of Open Systems: A 'Technology-Push, Need-Pull' perspective.'' Information Management 37, (2000): 229–39.

Crossing the quality chasm : A new health system for the 21st century (18 July 2001) by Institute of Medicine U.S.. Committee on Quality of Health Care in America.

Czaja, S., Charness, N., Fisk, A., Nair, S., Rogers, W., & Sharrit, J. (2006). Factors Predicting the Use of Technology: Findings From the Center for Research and Education on Aging and Technology Enhancement (CREATE). Psychology Aging, 21(2), 333-352. doi: 10.1037/0882-7974.21.2.333

Decker, S., Jamoom, E., Sisk, J. (2012). Physicians in nonprimary care and small practices and those age 55 and older lag in adopting electronic health record systems. Health Affairs, 31(5), 1108.

DesRoches, C. M., Campbell, E. G., Vogeli, C., Zheng, J., Rao, S. R., Shields, A. E., et al. (2010). Electronic health records' limited successes suggest more targeted uses. Health Affairs, 29(4), 639-646.

Donaldson, M. S., Kohn, L. T., & Corrigan, J. (2000). To err is human: Building a safer health system. Washington, D.C.: National Academy Press.

Durbin, J., and Watson, G. S. (1951) "Testing for Serial Correlation in Least Squares Regression, II." Biometrika 38, 159–179.

EHRWatch. (2011) AARP, Microsoft partner on PHR aimed at seniors. Retrieved on Aug 15, 2012 from http://www.ehrwatch.com/headline/aarp-microsoft-partner-phr-aimed-seniors.

Electronic health record functions differ between best and worst hospitals. (2011). The American Journal of Managed Care, 17(4), e121.

Exploring the business case for ambulatory electronic health record system adoption. (2011). Journal of Healthcare Management, 56(3), 169.

Farley, D. E., & Hogan, C. (1990). Case-mix specialization in the market for hospital services. Health Services Research, 25, 757-782.

Field, A. (2009). Discovering statistics using SPSS, 3rd ed. Sage. 266, 273-298.

Fumasoli, T., & Lepori, B. (2011). Patterns of strategies in Swiss higher education institutions. Higher Education, 61(2), 157-178. doi:10.1007/s10734-010-9330-x.

Ginn, G. O., Shen, J. J., & Moseley, C. B. (2011). Hospital financial position and the adoption of electronic health records. Journal of Healthcare Management, 56(5), 337-350.

Girosi F., Meili R.C., Scoville R. (2005). Extrapolating evidence of health information technology savings and costs. Retrieved on February 1, 2013 from http://www.rand.org/pubs/technical_reports/TR562z5/analysis-of-health-it.html

Harshberger, C., Harper, A., Carro, G., Spath, W., Hui, W., Lawton, J., & Brockstein, B. (2011). Outcomes of computerized physician order entry in an electronic health record after implementation in an outpatient oncology setting. Journal of Oncology Practice, 7(4), 233.

Health Information Technology and Economic and Clinical Health Act, 42 U.S.C. § 201 (2009).

Healthcare Financial Management Association (2006). Overcoming Barriers to Electronic Health Record Adoption. Retrieved on March 30, 2013 from http://www.vermontmanagedcare.org/Contribution/Providers/EHR/EHR_PDFs/2006%2002%2006%20HFMA%20Over.pdf

Henderson, J. W. (2002). Health Economics and Policy, 2nd ed. Southwestern Thompson Learning. pp.123, 153, 246, 430.

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

HIMSS. (2013). Electronic Health Record. Retrieved on February 1, 2013 from http://www.himss.org/asp/topics_ehr.asp

How the expansion of hospital systems has affected consumers. (2005). Health Affairs, 24(1), 213.

Hospital Management (2009). International Hospital Collaboration. Retrieved on March 6, 2013 from http://www.hospitalmanagement.net/ihf/publication_5_1.html

Incentives for the Use of Health Information Technology and Establishing the Position of the National Health Information Technology Coordinator, Executive Order 13335 (2004).

Jha, A. K., DesRoches, C. M., Campbell, E. G., Donelan, K., Rao, S. R., Ferris, T. G., . . . Blumenthal, D. (2009). Use of electronic health records in U.S. hospitals. New England Journal of Medicine, 360(16), 1628-1638. DOI: 10.1056/NEJMsa0900592.

Manitoba eHealth. (2012). EHR design. Retrieved on March 20, 2012 from http://www.manitoba-ehealth.ca/images/ehr_design.gif.

Meaningful Use Criteria, Stage 1, 42 C.F.R. § Vol 70 (140).

Menachemi, N., Prickett, C., & Brooks, R. (Jan-Mar, 2011). The use of physicial-patient email: a follow-up examination of adoption best-practice adherence 2005-2008. Journal of Medical Internet Research, 13(1), e23.

Menachemi, N., Powers, T., Brooks, R. (2011). Physician and practice characteristics associated with longitudinal increases in electronic health records adoption. Journal of Healthcare Management, 56(3), 183.

Menard, S. (1995). Coefficients of Determination for Multiple Logistic Regression Analysis. The American Statistician. 54(1) 2000

Meyers, R. (1990). Classical and modern regression with applications, 2nd ed. Duxbury: Thompson Learning.

Mitre. (2006). Electronic Health Records Overview. Retrieved on August 15, 2012 from http://www.himss.org/content/files/Code%20180%20MITRE%20Key%20Components%20of%20an%20EHR.pdf

Pfeffer, J., & Salancik, G. R. (1978 & 2003). The external control of organizations: A resource dependence perspective. New York: Harper & Row.

Porter, M. (1998). On Competition. Institute for Strategy and Competitiveness, Boston, Mass: Harvard Business School Press, (1998).

Porter, M. (2005). Redefining Health Care Creating Positive-sum Competition to Deliver Value. Boston, Mass: Harvard Business School, pp.2-5.

Progress toward meaningful use: Hospitals' adoption of electronic health records. (2011). The American Journal of Managed Care, 17, SP117.

Promoting electronic health record adoption among small independent primary care practices. (2011). The American Journal of Managed Care, 17(5), 353.

Reciprocal learning and chronic care model implementation in primary care: Results from a new scale of learning in primary care. (2011). BMC Health Services Research, 11(1), 44.

Renshaw, L., Kimberly, J., and Schwartz, J. ‘‘Technology Diffusion and Ecological Analysis: The Case of Magnetic Resonance Imaging.’’ In Innovations in Health Care Delivery: Insights for organization Theory, edited by Mick, S. San Francisco: Jossey-Bass, 1990.

Rogers. E. (1962). Diffusion of Innovations. New York: The Free Press

Rogers. E. (1995). Diffusion of Innovations, fourth ed. New York: The Free Press

Rogers, E. M. (2003). Diffusion of innovations, fifth ed. New York ; London : Free Press.

Sikka, V., Luke, R. D., & Ozcan, Y. A. (2009). The efficiency of hospital-based clusters: Evaluating system performance using data envelopment analysis. Health Care Management Review, 34(3), 251-261.

Tabachnick, B., & Fidell, L. (2007). Using Multivariate Statistics, fifth ed.New York, Pearson Education, Inc.

Wang, B., Wan, T. T. H., Burke, D., Bazzoli, G., & Lin, B. Y. J. (2005). Factors influencing health information system adoption in American hospitals. Health Care Management Review, 30(1), 44-51.

Wolf, L., Harvell, J., Jha, A. (2010). Hospitals ineligible for federal meaningful-use incentives have dismally low rates of adoption of electronic health records. Health Affairs, 31(3), 505.

Wu, I.,Kuo, Y. (Dec, 2012). A Balanced Scorecard Approach in Assessing IT Value in Healthcare Sector: An Empirical Examination. Journal of Medical Systems, 36(6), pp. 3583-3596.

Yeager, V., Menachimi, N., Brooks, R. (2010). EHR adoption among doctors who treat the elderly. (2010). Journal of Evaluation in Clinical Practice, 16(6), 1103.

Zwanziger, J., Melnick, G. A., & Simonson, L. (1996). Differentiation and specialization in the California hospital industry 1983 to 1988. Journal of Medical Care, 343, 361-372.

Appendix A:

Terms and Acronyms Used in This Research

Term/Acronym	Definition
AHA	American Hospital Association
CDSS	Clinical Decision Support System – an interactive decision support system (DSS) Computer Software, which is designed to assist physicians and other health professionals with decision making tasks, such as determining diagnosis of patient data
Cluster	Two or more same-system hospitals located in the same local market or region (Porter, 1998)
Cluster Lead	A Multiple Hospital System with multiple affiliated hospitals within a cluster will most likely assume a cluster lead position
CMS	Center for Medicaid and Medicare Services
Competitiveness	A proximal measure of productivity of healthcare in one region[14]
CPOE	Computerized Provider Order Entry – a process of electronic entry of medical practitioner instructions for the treatment of patients (particularly hospitalized patients) under his or her care.
CPT-10	Current Procedural Terminology (trademark of the American Medical Association). The current version is CPT-10
EHR	Electronic Health Record (inter organization – fully interoperable)
EMR	Electronic Medical Record (limited to one organization – not interoperable)
HCO	Health Care Organization
HIMSS	Health Information Management Systems Society

[14] This definition is a derivative of Porter's book on health care competition (1998) and the Bureau of Labor and Statistics (BLS) identification of US regions for the measurement of productivity. Porter states that competition in health care in the US is local (proximal).

Term/Acronym	Definition
HL7	Health Level 7 – the global authority on standards for interoperability of health information technology with members in over 55 countries (www.hl7.org)
ICD-10	International Classification of Diseases version 10. An exponential increase in diagnosis codes from ICD-9. Deadline for US implementation is October 1, 2013.
Interdependence	A reciprocal relationship between distinct but mutually dependent entities (Porter, 1998)
LR	Long Run -- the conceptual time period in which there are no fixed factors of production as to changing the output level by changing the capital stock or by entering or leaving an industry
MHS	Multi-Hospital System
NHIN	Nationwide Health Information Network (also eHealth Exchange) -- a web-services based series of specifications designed to securely exchange healthcare related data
NIH	National Institute of Health
SR	Short Run -- the conceptual time period in which at least one factor of production is fixed in amount and others are variable in amount. Costs that are fixed, say from existing plant size, have no impact on a firm's short-run decisions, since only variable costs and revenues affect short-run profits.

Appendix B:

Reasons For Federal Interest In The EHR

Sec. 2. *Policy.* In fulfilling its responsibilities, the work of the National Coordinator shall be consistent with a vision of developing a nationwide interoperable health information technology infrastructure that:

Ensures that appropriate information to guide medical decisions is available at the time and place of care;
Improves health care quality, reduces medical errors, and advances the delivery of appropriate, evidence-based medical care;
Reduces health care costs resulting from inefficiency, medical errors, inappropriate care, and incomplete information;
Promotes a more effective marketplace, greater competition, and increased choice through the wider availability of accurate information on health care costs, quality, and outcomes;
Improves the coordination of care and information among hospitals, laboratories, physician offices, and other ambulatory care providers through an effective infrastructure for the secure and authorized exchange of health care information; and
Ensures that patients' individually identifiable health information is secure and protected.

Source: Presidential Documents, 2004
.

Appendix C:

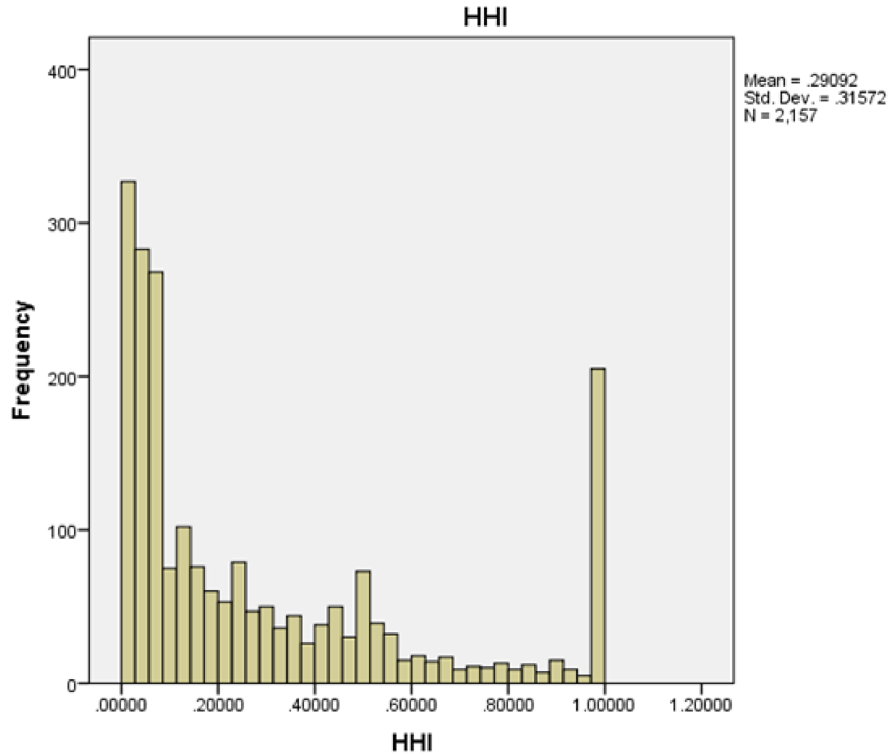
Data Frequency Tables

Statistics

		EHLTH_T2	HHI	MHSMEMB_T	HIE_ Participation	Ownership	CMS density	VA in CBSA	BSC	FTEH
N	Valid	2149	2157	2157	2099	2157	2157	2157	2157	2157
	Missing	8	0	0	58	0	0	0	0	0

Statistics

		GENHOS_T	Teach_T	2009 CMI	CEAMT_T	CPOE_Lab	CPOE_Rad	CPOE_Med	CPOE_ Consultation	CPOE_ Nurs_Ord
N	Valid	2157	2157	2154	1738	2157	2157	2157	2157	2157
	Missing	0	0	3	419	0	0	0	0	0



HHI is a continuous measure, so a frequency table is not provided.

MHSMEMB_T

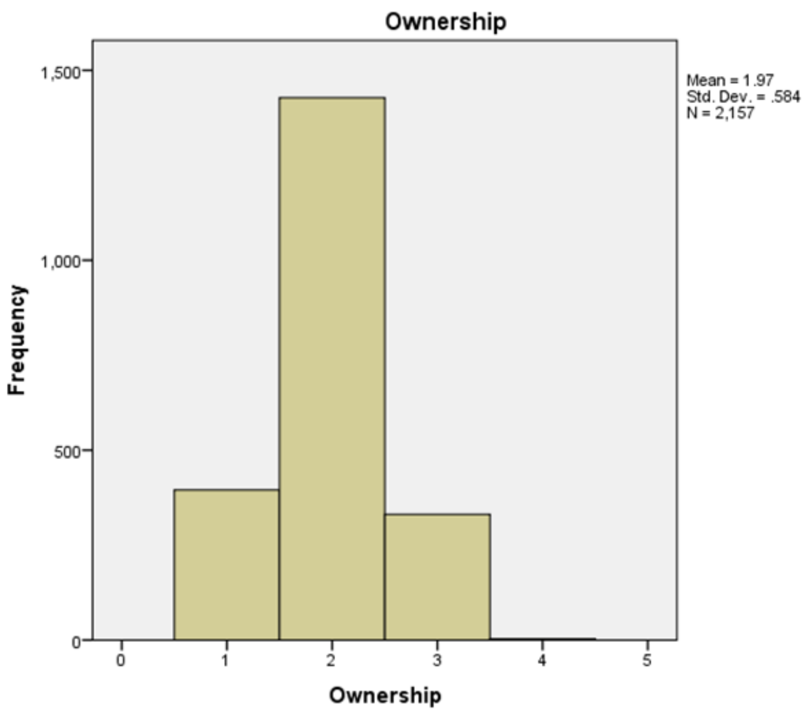
	Frequency	Percent	Valid Percent	Cumulative Percent
No MHS membership	957	44.4	44.4	44.4
Member of MHS	1200	55.6	55.6	100.0
Total	2157	100.0	100.0	

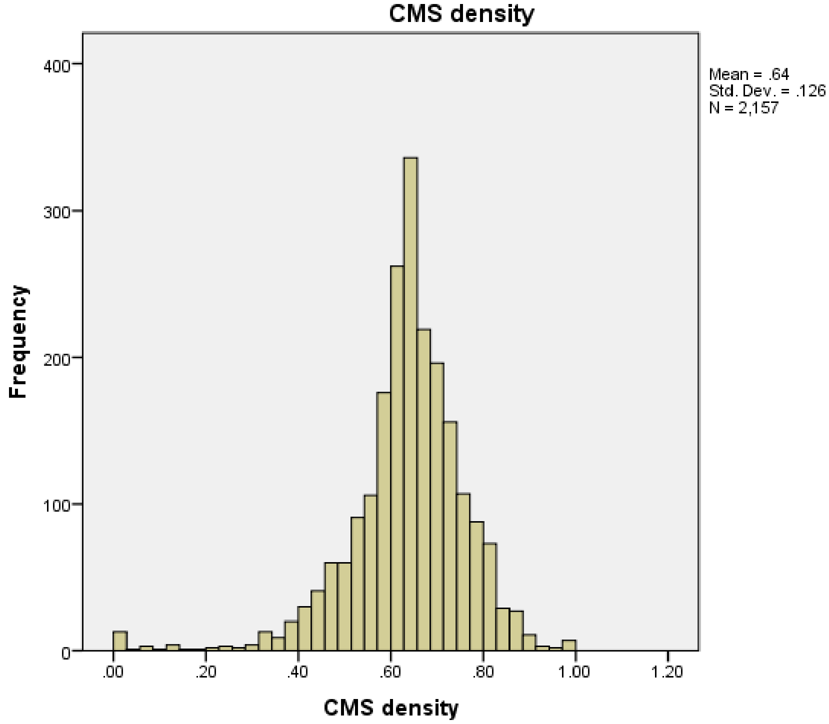
HIE_T

		Frequency	Percent	Valid Percent	Cumulative Percent
	Does not participate	1221	56.6	58.2	58.2
	Participates in HIE	878	40.7	41.8	100.0
	Total	2099	97.3	100.0	
Missing	System	58	2.7		
Total		2157	100.0		

Ownership (CNTRL)

	Frequency	Percent	Valid Percent	Cumulative Percent
Government, non-federal	395	18.3	18.3	18.3
Non-government, not-for-profit	1428	66.2	66.2	84.5
Investor-owned, for profit	331	15.3	15.3	99.9
Government, federal, non-VA	3	.1	.1	100.0
Total	2157	100.0	100.0	





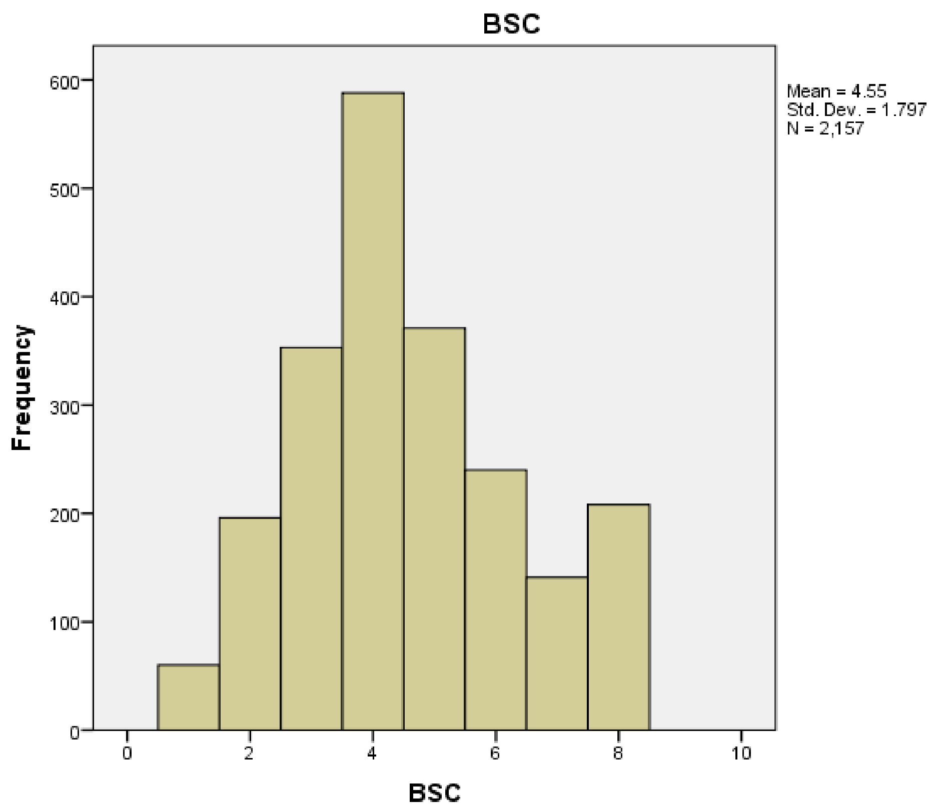
CMS density is a continuous measure, so a frequency table is not provided.

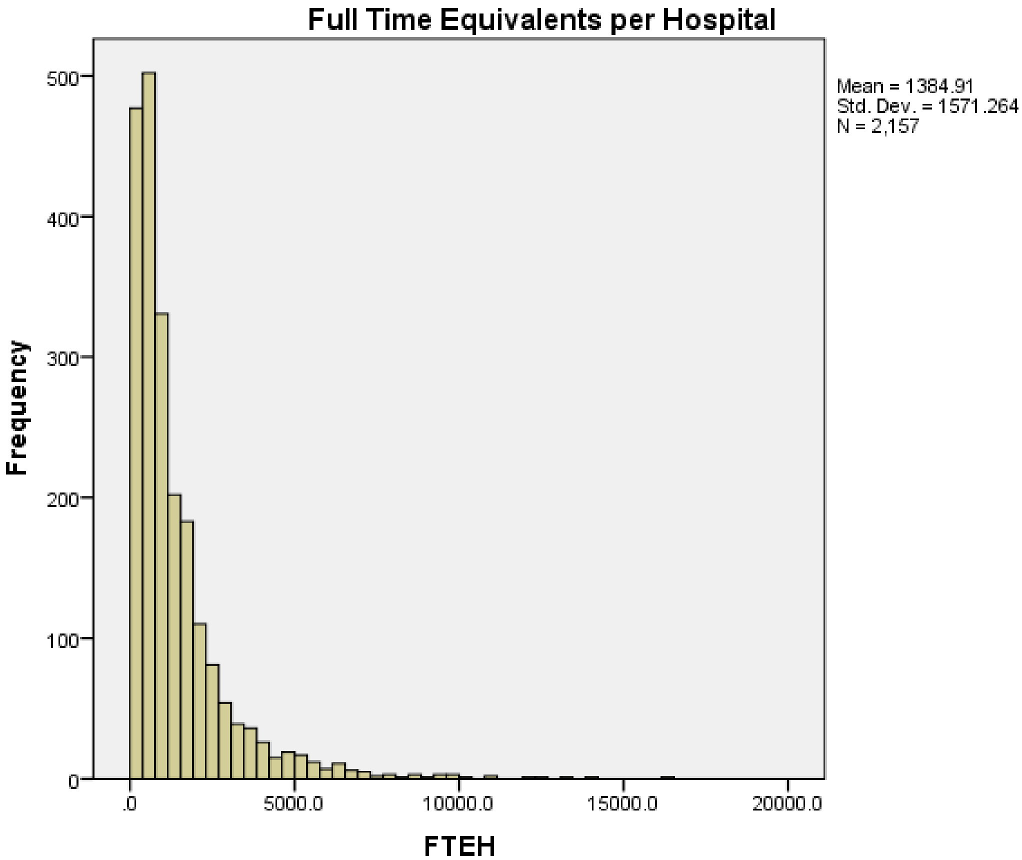
VA_local

	Frequency	Percent	Valid Percent	Cumulative Percent
No VA within CBSA	1237	57.3	57.3	57.3
VA within CBSA	920	42.7	42.7	100.0
Total	2157	100.0	100.0	

Bed Size

	Frequency	Percent	Valid Percent	Cumulative Percent
6-24 Beds	60	2.8	2.8	2.8
25-49 Beds	196	9.1	9.1	11.9
50-99 Beds	353	16.4	16.4	28.2
100-199 Beds	588	27.3	27.3	55.5
200-299 Beds	371	17.2	17.2	72.7
300-399 Beds	240	11.1	11.1	83.8
400-499 Beds	141	6.5	6.5	90.4
>=500 Beds	208	9.6	9.6	100.0
Total	2157	100.0	100.0	





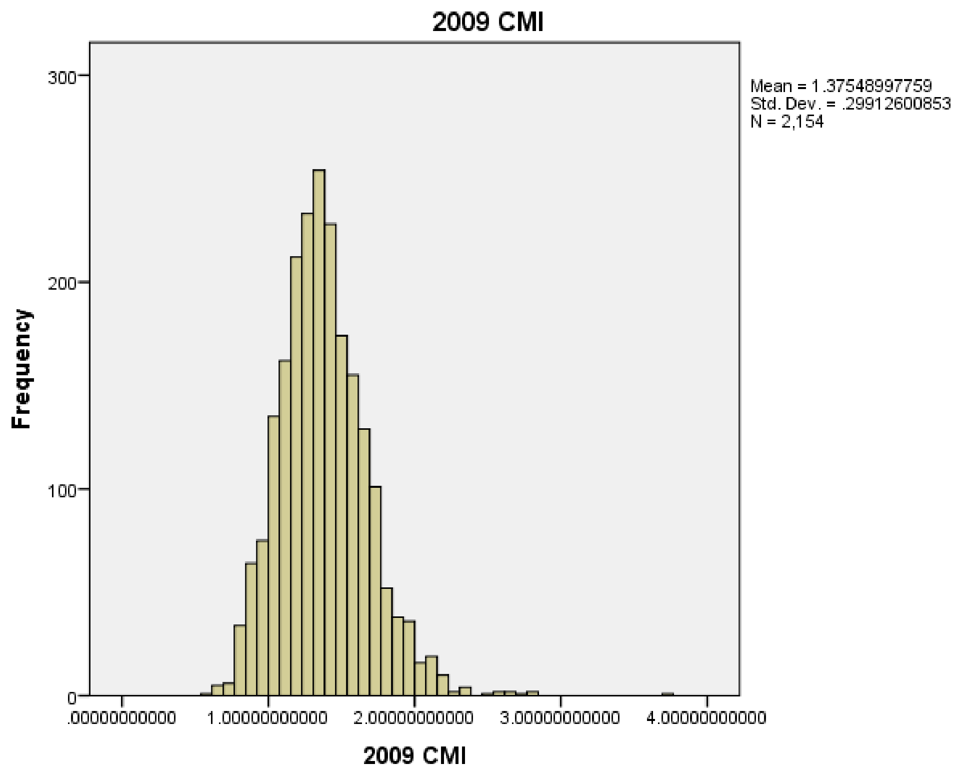
FTEH is a continuous measure, so a frequency table is not provided.

GENHOS

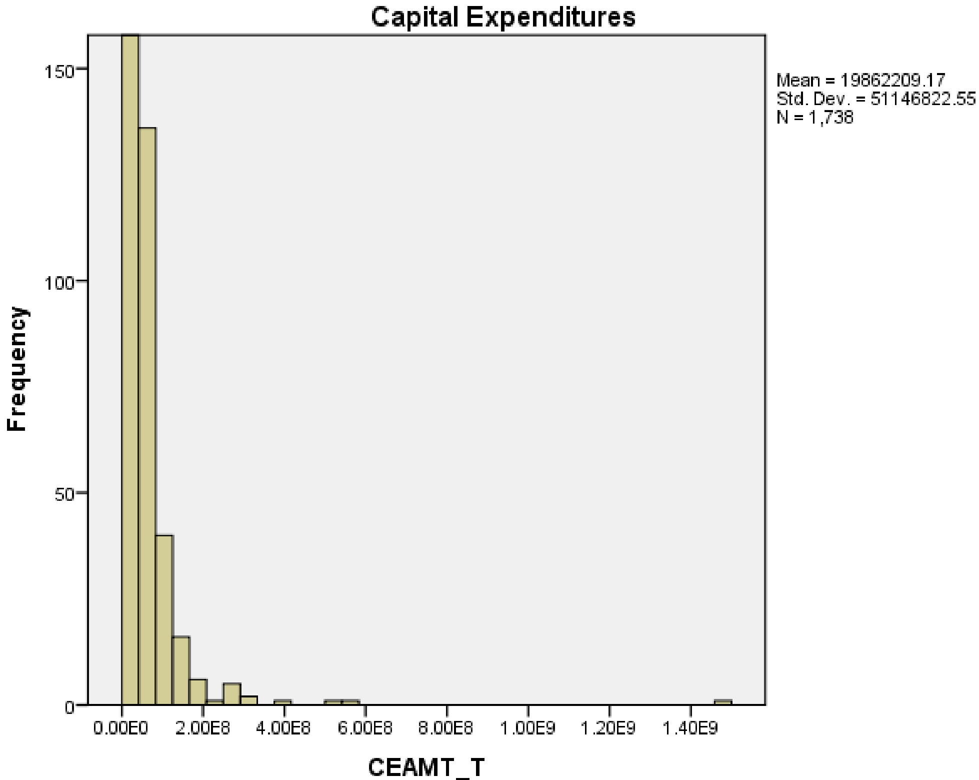
		Frequency	Percent	Valid Percent	Cumulative Percent
	non-general hospital	11	.5	.6	.6
	General hospital	1962	91.0	99.4	100.0
	Total	1973	91.5	100.0	
Missing	System	184	8.5		
Total		2157	100.0		

Teach_T

	Frequency	Percent	Valid Percent	Cumulative Percent
non-teaching HCO	1933	89.6	89.6	89.6
Teaching HCO	224	10.4	10.4	100.0
Total	2157	100.0	100.0	



CMI is a continuous measure, so a frequency table is not provided.



a. First bar rises to 1528

Capital expenditures is a continuous measure, so a frequency table is not provided.

EHLTH_T2

		Frequency	Percent	Valid Percent	Cumulative Percent
	not adopted HER	253	11.7	13.0	13.0
	partially to fully adopted	1690	78.3	87.0	100.0
	Total	1943	90.1	100.0	
Missing	System	214	9.9		
Total		2157	100.0		

CPOE_Lab

		Frequency	Percent	Valid Percent	Cumulative Percent
	Not implemented	1214	56.3	57.4	57.4
	Implemented	900	41.7	42.6	100.0
	Total	2114	98.0	100.0	
Missing	System	43	2.0		
Total		2157	100.0		

CPOE_Med

		Frequency	Percent	Valid Percent	Cumulative Percent
	Not implemented	1285	59.6	60.4	60.4
	Implemented	843	39.1	39.6	100.0
	Total	2128	98.7	100.0	
Missing	System	29	1.3		
Total		2157	100.0		

CPOE_Rad

		Frequency	Percent	Valid Percent	Cumulative Percent
	Not implemented	1239	57.4	58.0	58.0
	Implemented	896	41.5	42.0	100.0
	Total	2135	99.0	100.0	
Missing	System	22	1.0		
Total		2157	100.0		

CPOE_Consultations

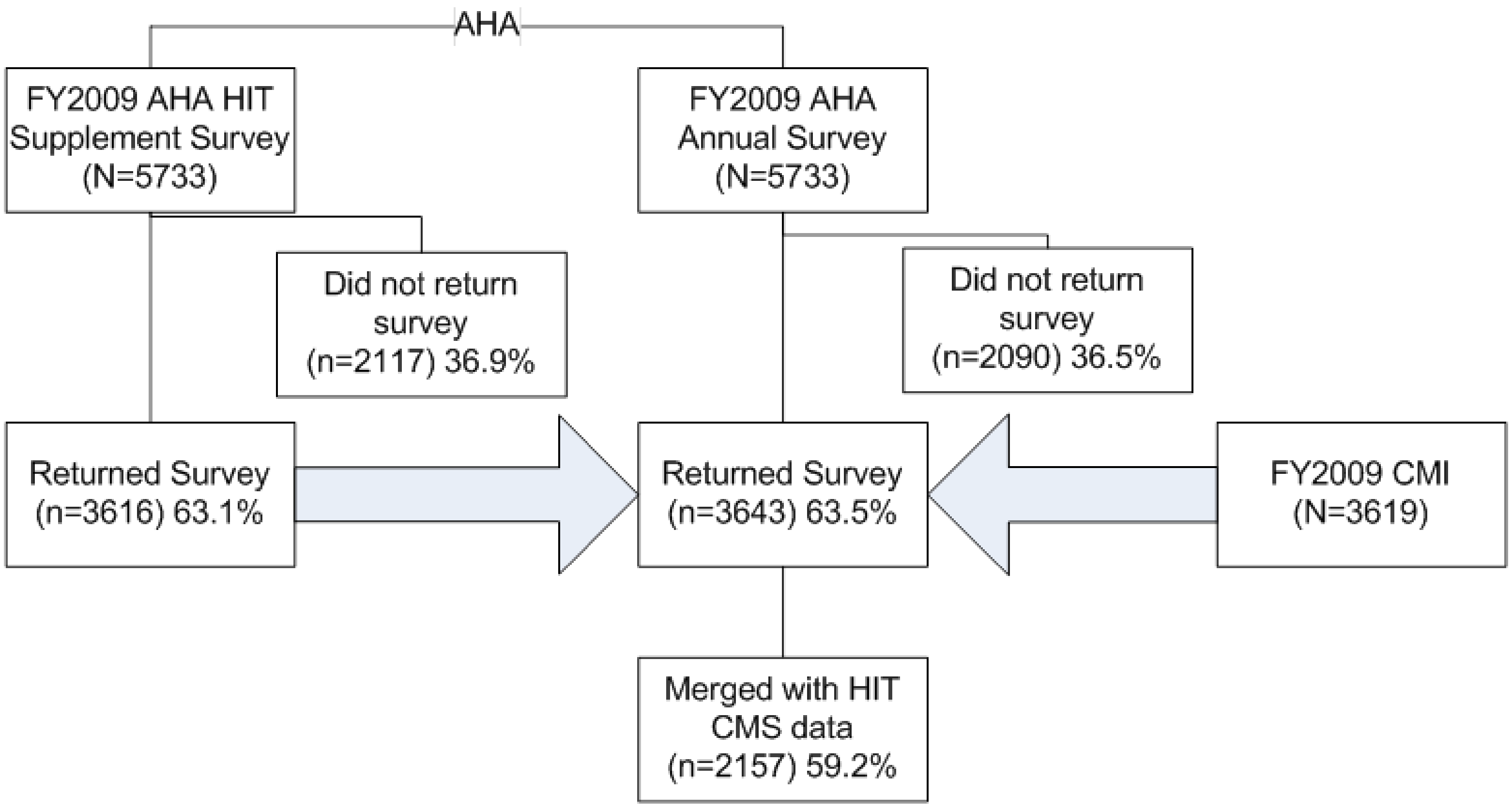
		Frequency	Percent	Valid Percent	Cumulative Percent
	Not implemented	1355	62.8	63.6	63.6
	Implemented	774	35.9	36.4	100.0
	Total	2129	98.7	100.0	
Missing	System	28	1.3		
Total		2157	100.0		

CPOE_Nursing

		Frequency	Percent	Valid Percent	Cumulative Percent
	Not implemented	1222	56.7	57.3	57.3
	Implemented	909	42.1	42.7	100.0
	Total	2131	98.8	100.0	
Missing	System	26	1.2		
Total		2157	100.0		

Appendix D:

Inclusion and Exclusion


AHA
FY2009 AHA HIT Supplement Survey (N=5733)
FY2009 AHA Annual Survey (N=5733)
Did not return survey (n=2117) 36.9%
Did not return survey (n=2090) 36.5%
Returned Survey (n=3616) 63.1%
Returned Survey (n=3643) 63.5%
FY2009 CMI (N=3619)
Merged with HIT CMS data (n=2157) 59.2%

Appendix E:

Tests of Multicollinearity

Collinearity Diagnostics

Dimension	Eigenvalue	Condition Index	Variance Proportions					
			(Constant)	HHI	CMS_ Density	FTEH	2009 CMI	CEAMT _T
1	4.219	1.000	0.00	0.02	0.00	0.01	0.00	0.01
2	1.001	2.053	0.00	0.08	0.00	0.05	0.00	0.38
3	0.464	3.014	0.00	0.61	0.00	0.07	0.00	0.30
4	0.272	3.937	0.00	0.27	0.01	0.59	0.00	0.30
5	0.035	10.954	0.00	0.02	0.46	0.18	0.30	0.00
6	0.008	23.297	0.99	0.00	0.52	0.10	0.69	0.00

a Dependent Variable: EHLTH_T2

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
HHI	0.948	1.054
CMS_Density	0.887	1.127
FTEH	0.533	1.877
2009 CMI	0.616	1.623
CEAMT_T	0.746	1.340

a Dependent Variable: EHLTH_T2

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	HHI	CMS_ Density	2009 CMI	CEAMT_T	FTEH
	1	4.248	1.000	.00	.01	.00	.00	.01	.01
	2	.990	2.072	.00	.08	.00	.00	.38	.05
	3	.462	3.033	.00	.57	.00	.00	.33	.07
	4	.262	4.025	.00	.30	.01	.00	.27	.57
	5	.031	11.779	.00	.03	.45	.33	.00	.20
	6	.007	24.451	.99	.00	.53	.66	.00	.10

a. Dependent Variable: CPOE_Lab

Appendix F:

Coefficients and Odds Ratios

		EHR		CPOE_Lab		CPOE_Rad		CPOE_Med		CPOE_Cons		CPOE_Nurs		95% C.I.for EXP(B)	
		B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	B	Exp(B)	Lower	Upper
x_1	HHI	0.38	1.46	-0.36	0.70	-0.35	0.70	-0.23	0.79	-0.23	0.80	-0.22	0.81	0.55	1.18
x_{2a}	MHSMEMB_T	0.40	1.50	0.10	1.11	0.16	1.17	0.13	1.14	0.13	1.14	0.02	1.02	0.82	1.27
x_{2b}	HIE_T	0.03	1.03	0.39	1.48	0.40	1.50	0.46	1.58	0.46	1.58	0.36	1.44	1.17	1.78
x_{2c}	CNTRL_gov	-0.15	0.86	0.18	1.20	0.22	1.24	0.15	1.16	0.14	1.15	0.09	1.10	0.83	1.46
x_{2d}	CNTRL_iofp	-0.96	0.39	-0.31	0.73	-0.36	0.70	-0.37	0.69	-0.68	0.51	-0.40	0.67	0.46	0.98
x_3	CMS_Density	0.59	1.81	-0.51	0.60	-0.60	0.55	-1.13	0.32	-0.85	0.43	-0.66	0.52	0.21	1.32
x_4	VA_local	0.05	1.05	0.08	1.09	0.10	1.11	0.17	1.19	0.22	1.24	0.06	1.06	0.82	1.36
x_{5a}	BSC_(6_24)	0.05	1.05	1.37	3.95	1.12	3.07	0.97	2.65	0.82	2.27	1.09	2.98	0.83	10.72
x_{5b}	BSC_(25_49)	-0.05	0.95	0.74	2.10	0.73	2.08	0.77	2.17	0.46	1.59	0.83	2.29	0.97	5.45
x_{5c}	BSC_(50_99)	-0.01	0.99	0.56	1.75	0.59	1.81	0.74	2.10	0.65	1.91	0.88	2.40	1.16	4.95
x_{5d}	BSC_(100_199)	-0.49	0.61	0.27	1.31	0.32	1.37	0.39	1.48	0.39	1.48	0.50	1.65	0.91	2.97
x_{5e}	BSC_(200_299)	-0.85	0.43	0.40	1.49	0.38	1.46	0.44	1.56	0.32	1.37	0.44	1.56	0.92	2.63
x_{5f}	BSC_(300_399)	-0.84	0.43	0.29	1.33	0.27	1.31	0.30	1.35	0.24	1.27	0.33	1.39	0.85	2.30
x_{5g}	BSC_(400_499)	-0.48	0.62	-0.13	0.88	-0.19	0.83	-0.11	0.90	-0.06	0.94	-0.18	0.83	0.49	1.41
x_{5h}	Ln_FTEH	0.79	2.21	0.52	1.68	0.52	1.67	0.53	1.70	0.56	1.75	0.63	1.87	1.38	2.53
x_{6b}	Teach_T	-0.04	0.96	0.86	2.37	0.86	2.37	0.88	2.41	0.76	2.14	0.76	2.14	1.39	3.28
x_{6c}	@2009CMI	0.05	1.05	-0.68	0.51	-0.64	0.53	-0.83	0.44	-0.63	0.53	-0.61	0.54	0.30	0.98
x_7	Ln_CMEAT	0.15	1.16	0.07	1.08	0.07	1.07	0.09	1.09	0.05	1.06	0.07	1.07	0.98	1.18
k	Constant	-5.78	0.00	-4.24	0.01	-4.24	0.01	-4.25	0.01	-4.42	0.01	-4.94	0.01		

*p<.1, **p<.05, ***p<.001

Vita

Clemens Scott Kruse was born on April 19, 1966 in Rockford Illinois. He graduated from California High School in Whittier, California. He received his Bachelor of Science in Engineering Psychology in 1991 from the United States Military Academy at West Point, New York. He received a Master of Business Administration with a concentration in the Management of Technology in 2004 from the University of Texas at San Antonio, and he received a Master of Science in Information Technology in 2005 from the same. He received a Master in Health Administration in 2005 from Baylor University. He has taught at the undergraduate and graduate levels for four years. He taught five years in the Graduate School at Baylor University, five years in the undergraduate school (online) at Capella University, two years in the graduate school at Trinity University, and one year in the graduate school at the University of the Incarnate Word. He has designed, used, and refined health information technology curriculum in nationally ranked graduate schools. He has taught a wide range of topics ranging from software design to medical and anatomical terminology. He worked in the healthcare technology industry in the federal sector for eleven years and was a US Army Officer for over 20 years. He is a board certified healthcare administrator and Fellow of the American College of Healthcare Executives, a board certified healthcare information manager through the Health Information Management Systems Society, a certified computer security manager through the Computer Technology Information Association, a certified systems engineer through Microsoft, a certified Six Sigma Green Belt and senior member at the American Society for Quality, and he received a Federal Chief Information Officer Certificate in 2010 from National Defense University. Scott Kruse is the principal of Kruse Consulting Services where he provides consulting services for the US Air Force Medical Service Agency.