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Meaningful Use of Electronic Health Records for Population Health Management in U.S. Acute Care Hospitals

Niodita Gupta
University of Nebraska Medical Center

MEANINGFUL USE OF ELECTRONIC HEALTH RECORDS FOR POPULATION HEALTH MANAGEMENT IN U.S. ACUTE CARE HOSPITALS

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Niodita Gupta

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Supervisory Committee:

Preethy Nayar, M.D., Ph.D.

Li-Wu Chen, MHSA, Ph.D.

Jungyoon Kim, Ph.D.

Fang Yu, Ph.D.

Dedicated to

My mother, Sulabha Gupta

And my father, Ramchandra Gupta

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Niodita Gupta, PhD

University of Nebraska Medical Center, 2017

Advisor: Preethy Nayar, MD, PhD

ABSTRACT

Population health management (PHM) is used to identify the needs of a population and to align strategies to improve the health of the population through care coordination. The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 emphasized the meaningful use (MU) of electronic health records (EHRs) to improve clinical and population health outcomes. The American Recovery and Reinvestment Act (ARRA) of 2009 approved the EHRs incentives program for eligible hospitals to demonstrate the MU of EHRs. Further, eligible hospitals which failed to demonstrate the MU of EHRs could face payment adjustments. Given a heightened focus on MU of EHRs for PHM and a reimbursement policy that incentivizes the MU of EHRs for PHM, EHRs can play an important role in PHM. Therefore, it is important to study the correlates of MU of EHRs for PHM in hospitals.

This study examined the organizational and environmental correlates of the implementation of PHM objectives of MU of EHRs for PHM and the level of MU of EHRs for PHM in acute care hospitals in the United States (U.S). Three of the four dependent variables examined in this study were based on the three PHM objectives of MU of EHRs: 1) submission of electronic data to immunization registries, 2) submission

of electronic data on reportable laboratory results to public health agencies, and 3) submission of electronic syndromic surveillance data to public health agencies. The level of MU of EHRs for PHM was a composite measure created using the aforementioned three PHM objectives.

This study used resource dependency theory to derive the conceptual model based on its constructs of munificence, uncertainty, and interdependence. This study used an observational, retrospective, multiple correlational study design with a one-year lag for independent variables to address the research objectives. The data for this study were obtained from the American Hospital Association Annual Survey Database 2013, Area Health Resource Files 2015-2016, Centers of Medicare and Medicaid Stage 1 and Stage 2 MU datafiles for year 2014, and state health policy levers compendium 2011-2013. Due to the hierarchical nature of the data, mixed effects regression models were used for the analyses. The study found the munificence construct operationalized as the size of the hospital, uncertainty construct operationalized as market competition, and interdependence construct operationalized as system membership, ownership control, and the stage of MU implementation of EHRs to be significantly associated with the MU of EHRs for PHM.

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CHAPTER ONE: INTRODUCTION

Background and Statement of the Problem

Following the introduction of the Triple Aim framework in 2008 (Berwick, Nolan, & Whittington, 2008) and the implementation of the Patient Protection and Affordable Care Act (PPACA) in 2010 (Patient Protection and Affordable Care Act, 2010), population health management (PHM) gained focus and momentum. The triple aim framework proposed by Berwick, Nolan, & Whittington (2008) suggested that the three aims of (1) improving the experience of care, (2) improving the health of populations, and (3) reducing per capita costs of healthcare are necessary to improve the U.S. healthcare system. Under the PPACA, the National Quality Strategy was formed to "promote quality health care in which the needs of patients, families, and communities guide the actions of all those who deliver and pay for care" (Department of Health and Human Services [DHHS], 2011, March, p. 1). PHM can be described as identifying the healthcare needs of a service area and aligning strategies to improve health outcomes of the entire population through care coordination (Kapp, Oliver & Simoes, 2016; Hardcastle et al., 2011; Population Health Alliance, n.d.). PHM has shifted the focus of health care from individual clinical care to integrated population health. PHM also forms the core of value-based models which are emerging in the health care market (Kizer, 2015; Health care transformation task force, 2015). Value-based programs reward the healthcare providers with incentive payments based on the quality of care provided by them (Centers for Medicare & Medicaid Services [CMS], n.d.). This makes it important for the hospitals to address and promote PHM.

The Health Information Technology for Economic and Clinical Health (HITECH Act) of 2009 emphasized the use of electronic health records (EHRs) (U.S. Department of Health and Human Services [US DHHS], n.d.). The HITECH Act was aimed at improving clinical and population health outcomes, increasing transparency and efficiency, empowering individuals, and providing robust healthcare by using the EHRs meaningfully (HealthIT.gov, 2015, February 6). The meaningful use (MU) of EHRs focused on improving the quality, safety, efficiency, care coordination, and population health, and maintaining the privacy and safety of the health information (HealthIT.gov, 2015, February 6). Through the American Recovery and Reinvestment Act of 2009, eligible hospitals and healthcare professionals could receive incentives for demonstrating MU of EHRs (CMS, 2016, November 22). Additionally, eligible hospitals which do not demonstrate MU of EHRs could receive payment adjustments through CMS (Medicare and Medicaid Programs Electronic Health Record Incentive Program-Stage 2, 2012).

The HITECH Act proposed to achieve MU in three stages. During the Stage 1 of meaningful use of EHRs, data would be captured and shared through EHRs; the Stage 2 of meaningful use of EHRs would help to advance clinical process; and the Stage 3 of meaningful use of EHRs would help to improve health outcomes (HealthIT.gov, 2015, February 6). The Stage 1 of MU of EHRs was first implemented in 2011 while the Stage 2 of MU of EHRs was first implemented in 2014 (CMS, 2012, August). CMS established a rule which requires the hospitals to progress to the next stage of MU of EHRs after demonstrating the MU of EHRs for two years for the current stage (CMS, 2012, August). There are hospitals which have started the implementation of MU of EHRs in the consequent years (i.e. after 2011) and they also follow the CMS' rule of progressing to the next stage after demonstrating the current stage of MU of EHRs for two years. This study focuses on the Stage 1 and the Stage 2 of MU of EHRs since the Stage 3 implementation does not begin until 2017 (Medicare and Medicaid Programs; Electronic Health Record Incentive Program—Stage 3 and Modifications to Meaningful Use in 2015 Through 2017, 2015, October 16).

Stage 1 and Stage 2 have specific objectives that the eligible hospitals are required to meet in order to be eligible for incentives. Each stage has a set of core objectives which are mandatory for all eligible hospitals and a set of menu objectives which allow the eligible hospitals to make a choice. The eligible hospitals must choose and meet a pre-determined number of objectives from the list of menu objectives proposed for each stage. In order to obtain incentives for Stage 1, eligible hospitals are required to meet all 14 core objectives and five objectives from a list of ten menu objectives (CMS, 2010). Three PHM objectives were included in the list of ten menu objectives in Stage 1. These were: (1). Capability to submit electronic data to immunization registries or Immunization Information Systems and actual submission in accordance with applicable law and practice, (2). Capability to submit electronic data on reportable (as required by state or local law) lab results to public health agencies and actual submission in accordance with applicable law and practice, and (3). Capability to submit electronic syndromic surveillance data to public health agencies and actual submission in accordance with applicable law and practice. Although the eligible hospitals have a choice of five objectives from a list of ten, at least one of the five objectives demonstrated has to be a PHM objective. For Stage 2, eligible hospitals are required to meet all 16 core objectives and three menu objectives from a list of six objectives (CMS, 2012, August). In Stage 2, the three PHM objectives become core objectives: (1). Submit electronic data to immunization registries, (2). Submit electronic data on reportable lab results to public health agencies, and (3). Submit electronic syndromic surveillance data to public health agencies. This mandate of meeting the three PHM objectives in Stage 2 further highlights the importance of PHM.

Various studies have observed that the adoption and implementation of EHRs can help to improve the quality of care provided to the patients by reducing the number of medication errors (Bates et al., 1999; Shulman, Singer, Goldstone, & Bellingan, 2005; Zlabek, Wickus, & Mathiason, 2011), the number of laboratory tests and radiology examinations (Zlabek et al., 2011), charges per admission (Tierney, Miller, Overhage, & McDonald, 1993), bed charges (Tierney et al., 1993), diagnostic test charges (Tierney et al., 1993), drug charges (Tierney et al., 1993), and the use of evidence-based medicine (Paul et al., 2015). The adoption of EHRs have also increased patient satisfaction levels (Adler-Milstein, Everson, & Lee, 2015; Freeman, Taylor, & Adelman, 2009; Liu, Luo, Zhang, & Huang, 2013).

Further, the use of EHRs for PHM have enabled faster and greater surveillance of the population for diseases (Gluskin, Mavinkurve, & Varma, 2014). The data collected by registries have the potential to track adverse events and to advance research (Savel & Foldy, 2012). A report by the Institute of Medicine (IOM) Committee on Data Standards for Patient Safety (2003) named data reporting and PHM as one of the eight key functionalities of EHRs. PHM interventions that used EHRs for identification of patients who are overdue for colorectal cancer screening have resulted in higher screening rates and reduction in health disparities (Berkowitz et al., 2015). This further strengthens the case for using EHRs for PHM.

Given the current scenario of EHRs incentives program, payment adjustments following the HITECH and ARRA acts, the Triple Aim framework, the IOM report, and the shift towards value-based payments, it will soon become necessary for the hospitals to implement PHM functionalities of EHRs to survive in the market. Various factors could facilitate or hinder the use of EHRs for PHM. This poses the question – what factors are associated with the use of EHRs for PHM? A review of the literature found that that there is very scarce literature on the use of EHRs for PHM. Most of the studies have focused on interventions (which identified at-risk patients and provided targeted support or screening) which were implemented using EHRs and the outcomes of the intervention. However, no prior study has examined the factors that may be associated with the MU of EHRs for PHM. Answering this research question can provide insights to policymakers about the factors that can inhibit or encourage the wide spread use of PHM. This study aimed to examine the organizational and environmental factors associated with the MU of EHRs for PHM.

Purpose of the Study

The aims of this study were:

1. To examine the organizational and environmental factors that are associated with the implementation of PHM objectives of MU of EHRs in acute care hospitals in the United States (U.S.).

2. To examine the organizational and environmental factors that are associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S.

The first aim of this study is to examine the organizational and environmental factors that are associated with the implementation of each of the three PHM objectives of MU of EHRs in acute care hospitals in the U.S. The second aim of the study addresses the three PHM objectives together to measure the level of MU of EHRs for PHM. For the purpose of this study, the level of MU of EHRs for PHM is defined based on the number of PHM objectives that are met by the hospital. The level of MU of EHRs for PHM is categorized as: 1) no MU of EHRs for PHM, 2) minimum level of MU of EHRs for PHM, 3) moderate level of MU of EHRs for PHM, and 4) comprehensive level of MU of EHRs for PHM. If none of the three PHM objectives were implemented, the level of MU of EHRs for PHM was defined as no MU of EHRs for PHM. If only one of the three PHM objectives were implemented, the level of MU was defined as minimum level of MU of EHRs for PHM. If two of the three PHM objectives were implemented, the level of MU was defined as moderate level of MU of EHRs for PHM. If all three of the PHM objectives were implemented, the level of MU was defined as comprehensive level of MU of EHRs for PHM.

Research Questions

This study addresses the following research questions:

1. What are the organizational and environmental factors associated with the implementation of the PHM objectives of MU of EHRs in acute care hospitals in the U.S.?

2. What are the organizational and environmental factors associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S.?

Overview of the Theoretical Framework

This study used the resource dependency theory to develop the conceptual framework to answer the research questions. The resource dependency theory was proposed by Pfeffer and Salancik in 1978. Resource dependency theory posits that organizations require resources to operate and survive in the market. However, no organization is self-sufficient in terms of resources and has to depend on the environment for its resources. Organizations are thus subject to environmental constraints. In such conditions, organizations are dependent on other entities for resources and the organization’s strategic behavior is oriented towards gaining control of critical resources. Organizations strategize to acquire and control more resources and reduce their dependence on the environment.

The resource dependency theory has three key constructs: munificence, uncertainty, and interdependence. Munificence refers to the availability of the resources in the environment (Pfeffer & Salancik, 1978). The resources needed by the organization may be abundant or scarce in the environment. Abundant resources give the organizations more flexibility in their operations and services because they don’t have to compete extensively to acquire those resources (Menachemi, Shin, Ford, & Yu, 2011). However, if the resources are scarce in the environment, organizations have to strategize to obtain these resources and remain viable in the market. Uncertainty refers to the variability and complexity in acquiring resources from the environment (Pfeffer &

Salancik, 1978). The market environment is dynamic owing to organizations entering and exiting from the market. This dynamic environment generates competition in the market which may lead to an uncertainty of resources. There are a limited number of resources in the market and organizations have to compete with each other to obtain their share of the resources. In order to compete and stay ahead in the market, organizations may strategize their behavior to obtain more resources (Menachemi, Shin, Ford, & Yu, 2011). Interdependence refers to the dependency of organizations on one another to secure the necessary resources from the environment and stay viable (Pfeffer & Salancik, 1978). An organization may form interdependent relationships with other organizations to gain power in the market which is necessary to secure resources. An organization may be dependent on other constituents in the market for the necessary resources. As the dependence of the focal organization on other entities increases, the focal organization becomes more complaint (Weech-Maldonado, Qaseem, & Mkanta, 2009). Organizations strategize their behavior to increase their power in the market and reduce their dependency on other organizations or to increase the dependency of other organizations on themselves.

This study focuses on the strategic behavior of acute care hospitals in the U.S. As resource dependency theory proposes, this study assumes that acute care hospitals in the U.S. have to depend on their environment for necessary resources. Acute care hospitals may choose to implement MU of EHRs for PHM as a strategy to obtain more resources from the environment. Based on this perspective, a conceptual framework was developed to operationalize the key constructs of resource dependency theory: munificence, uncertainty, and interdependence.

Overview of the Conceptual Model

Using the resource dependency theory, a conceptual model was developed. The key behavioral construct was implementation of organizational innovation which is operationalized as the implementation of MU of EHRs for PHM. The causal constructs are based on the constructs of resource dependency theory: munificence, uncertainty, and interdependence. Munificence, i.e. availability of the resources, was operationalized as the size of the hospital, membership of multi-hospital system, and community wealth of the market. Uncertainty, i.e. the variability in the environment, was operationalized as the degree of market competition. Interdependence, i.e. interdependent relationships of the organization, was operationalized as the ownership of the hospital, public-payer mix of the hospital, the stage of implementation of MU of EHRs, and the state regulatory environment. Based on this conceptual model, research hypotheses were proposed.

Research Hypotheses

The following research hypotheses were developed and tested in this study:

Munificence

H1a: All else being equal, larger acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to smaller acute care hospitals.

H1b: All else being equal, larger acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to smaller acute care hospitals.

H2a: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are not members of multi-hospital system.

H2b: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to have higher level of MU of EHRs for PHM, as compared to those that are not members of multi-hospital system.

H3a: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to implement the PHM objectives of MU of EHRs, as compared to those located in the areas of lower community wealth.

H3b: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to have higher level of MU of EHRs for PHM, as compared to those located in the areas of lower community wealth.

Uncertainty

H4a: All else being equal, acute care hospitals located in more competitive markets are more likely to implement the PHM objectives of MU of EHRs, as compared to those located in lesser competitive markets.

H4b: All else being equal, acute care hospitals located in more competitive markets are more likely to have higher level of MU of EHRs for PHM, as compared to those located in lesser competitive markets.

Interdependence

H5a: All else being equal, for-profit acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to not-for-profit acute care hospitals.

H5b: All else being equal, for-profit acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to not-for-profit acute care hospitals.

H6a: All else being equal, government hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to the not-for-profit acute care hospitals.

H6b: All else being equal, government hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to the not-for-profit acute care hospitals.

H7a: All else being equal, acute care hospitals that have a higher public payer mix are more likely to implement the PHM objectives of MU of EHRs, as compared to those that have a lower public payer mix.

H7b: All else being equal, acute care hospitals that have a higher public payer mix are more likely to have higher level of MU of EHRs for PHM, as compared to those that have a lower public payer mix.

H8a: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to implement PHM objectives of MU of EHRs, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

H8b: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to have a higher level of MU of EHRs for PHM, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

H9a: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are in states with no laws/policies for public health data reporting.

H9b: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to have higher level of MU of EHRs for PHM, as compared to those that are in states with no laws/policies for public health data reporting.

Research Plan

This study used a retrospective cross-sectional multi-correlational research design to address the questions of this research. The unit of analysis for this study was an individual acute care hospital in the U.S. The scope of this study was limited to only non-federal, non-critical access, acute care hospitals in the U.S. This study only included the hospitals located in the 50 U.S. states and the District of Columbia. The study used American Hospital Association Annual Survey Database 2013 (American Hospital Association, 2014), Centers for Medicare and Medicaid Services Stage 1 and Stage 2 meaningful use data files 2015 (CMS, 2016, October 27), Area Health Resource Files 2015-2016 (Bureau of Health Workforce, 2016), and the state HIT policy levers compendium file 2011-2013 (HealthIT.gov, 2016, July 26) to obtain the data necessary for this study. The data for the year 2013 were used for all the independent variables except one (which was measured in year 2014) while the data for the year 2014 were used for the dependent variables. The independent variables were lagged by one year to address the issue of temporal precedence i.e., the cause preceding the effect.

The dependent variables were derived from the three PHM objectives of MU of EHRs. The dependent variables in this study are: (1). Use of EHRs to submit electronic data to immunization registries, (2). Use of EHRs to submit electronic data on reportable laboratory results to public health agencies, (3). Use of EHRs to submit electronic syndromic surveillance data to public health agencies, and (4). Level of MU of EHRs for

PHM. The level of MU of EHRs for PHM is a composite measure that was created for this study by combining the three PHM objectives of MU of EHRs. The independent variables were derived from the conceptual model developed using the resource dependency theory. The independent variables in this study are: per capita personal income of people in the market area, size of the hospital, system membership of the hospital, Herfindahl-Hirschman Index, public payer mix of the hospital, ownership of the hospital, stage of implementation of MU of EHRs, and the state laws/policies. This study controlled for geographic location of the hospital and the teaching status of the hospital.

This study used SAS 9.4 for data manipulation (SAS Institute Inc., Cary, North Carolina) and STATA 14.0 for statistical analysis (StataCorp LP., College Station, TX). Descriptive analyses such as mean, median, minimum, maximum, and standard deviation were conducted for each continuous variable, and frequency and percentage were calculated for each categorical variable. One sample t-test and one sample test of proportions were conducted to compare the study sample and the study population. The three dependent variables, 1. Use of EHRs to submit electronic data to immunization registries, 2. Use of EHRs to submit electronic data on reportable laboratory results to public health agencies, 3. Use of EHRs to submit electronic syndromic surveillance data to public health agencies, are dichotomous variables categorized as yes and no. The nature of the data is hierarchical where all hospitals are nested within states; this may cause correlations between observations. Hence, mixed effects logistic regression analyses were conducted for each of these three dependent variables. The fourth dependent variable, the level of MU of EHRs for PHM, has four categories: no MU of EHRs for PHM, minimum level of MU of EHRs for PHM, moderate level of MU of

EHRs for PHM, and comprehensive level of MU of EHRs for PHM. The nature of data is also hierarchical and hence, mixed effects multinomial logistic regression was conducted for this dependent variable.

Outline of the Ensuing Chapters

Chapter two presents an overview of PHM and EHRs, including the HITECH Act and the EHRs incentives program. It also describes the value of EHRs and the use of EHRs for PHM. It further summarizes the facilitators and barriers associated with the adoption and implementation of EHRs. Chapter three provides an overview of innovation and implementation of innovation. It also describes the resource dependency theory which is used to conceptualize this study. It further illustrates and describes the conceptual model and then states and discusses the research hypotheses which were formed based on the conceptual model. Chapter four describes the study design, the study sample, the data sources, the key variables and their measurement. It also discusses the statistical analytical strategy. Chapter five presents the results of the data analysis. Chapter six discusses the interpretation of the findings with respect to policy, practical, and theoretical implications. It also discusses the limitations of the study and potential for future research.

CHAPTER TWO: LITERATURE REVIEW

This chapter focuses on the theme of this study, i.e. population health management (PHM) and electronic health records (EHRs). This chapter defines these two concepts and discusses the value of EHRs and the use of EHRs for PHM. This chapter then summarizes the literature on adoption and implementation of EHRs. This chapter further describes the laws around EHRs and the EHRs incentives program.

Population Health Management

The triple aim framework proposed by Berwick, Nolan, & Whittington (2008) suggested that the three aims of (1) improving the experience of care, (2) improving the health of populations, and (3) reducing per capita costs of healthcare are necessary to improve the U.S. healthcare system. Berwick et al. (2008) drew attention towards PHM by suggesting efficient and equitable resource allocation for various population groups in their triple aim framework. They compared acute care (which is a response to individual patient needs) with identifying patterns and implementing preventive efforts (which is a response to population health), thus further elaborating the importance of PHM. PHM shifts the focus of health care from clinical care to integrated care to improve population health (Hardcastle, Record, Jacobson, & Gostin, 2011). PHM further gained the limelight after the Patient Protection and Affordable Care Act (PPACA) of 2010 created provisions to improve the quality of health care through the National Quality Strategy (DHHS, 2011, March). The National Quality Strategy aims to “promote quality health care in which the needs of patients, families, and communities guide the actions of all those who deliver and pay for care” (DHHS, 2011, March, p. 1). The three specific goals of the National

Quality Strategy are better care, healthy people/healthy communities, and affordable care. Through these goals, National Quality Strategy focuses on PHM.

PHM has various definitions. Some of the key definitions are as follows:

Population health management is a tool “used to describe a variety of approaches developed to foster health and quality of care improvements while managing costs” (McAlearney, 2003, p.3).

“Population health management (PHM) is a nebulous term used to describe identifying the health needs of a health care service area and aligning those with targeted strategies to improve health outcomes” (Kapp, Oliver & Simoes, 2016, p.1).

“Population health management is an approach that aims to improve the health status of the entire population through coordination of care across the continuum of health in order to improve behavioral/lifestyle, clinical and financial outcomes” (Population Health Alliance, n.d.).

All of these definitions of PHM clearly indicate a shift in the focus from individual level care to population level care. Barnes et al. (2014) found that PHM can have a big impact on the community by decreasing unnecessary disease burden and improving the overall health status of the community.

The era of managed care and fee-for-service is ending, and value-based payments are gaining momentum. Value-based payment programs reward the healthcare providers with incentive payments based on the quality of care provided by them (CMS, n.d.). These value-based payment programs are a part of the National Quality Strategy which is discussed above. The value-based payment programs also support the three aims of the

National Quality Strategy, thus emphasizing PHM. By 2018, half of Medicare spending other than managed care will be based on value-based payment models (Kizer, 2015). The Health Care Transformation Task Force which is formed by a group of large employers, payers, and healthcare systems also announced the shift of 75 percent of their business to value-based care by 2020 (Health care transformation task force, 2015). Kizer (2015) observed that in this changing environment towards value-based care, PHM is a necessary task for the health system and will be “a requisite core competency” for the success of health care systems. Successful PHM calls for clinical integration across providers, health care settings, conditions, and time (Kizer, 2015). PHM starts with the integration of clinical and non-clinical data. This integration provides the physicians with meaningful data which can be used to deliver higher quality care to their patients. Other than quality of care, substantial financial savings are also associated with PHM. Grossmeier et al. (2013) found two years of PHM program and one year of disease management program yielded a return-on-investment of $3 in savings for every $1 spent. Thus, PHM is critically important and health care providers will be increasingly tasked to adopt PHM.

Electronic Health Records

Electronic Health Record (EHR) is defined as “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" (Healthcare Information and Management Systems Society [HIMSS], n.d.). EHRs are basically computerized versions of patients' paper charts; however, implementing all features of EHRs can make them "real-time patient-centered records" (HealthIT.gov, 2014, May 21). EHRs have the capacity to capture, transmit, receive, store, retrieve, link, and manipulate multimedia data for healthcare services, quality management, and outcome reporting (National Institutes of Health, 2006). EHRs contain the patient's medical history, medications, immunization records, allergies, laboratory, and radiology tests and results. It helps to bring all information needed about a patient in one place and a healthcare provider can view the patient's records from anyplace at any time. This enables the provider to view the most accurate information even in cases of emergencies (HealthIT.gov, 2013, March 16).

The Value of Electronic Health Records. Obtaining health information through EHRs has reduced the amount of missing clinical data as compared to the paper charts (Smith et al., 2005). Using EHRs for results management has reduced the number of duplicative tests (Walker, Pan, Johnston, & Adler-Milstein, 2005). Additionally, EHRs can provide access to evidence-based tools that can help the providers in decision-making (HealthIT.gov, 2013, March 16). Thus, proper implementation of EHRs can provide complete, timely, and sophisticated clinical information and support to the physicians and thus improve quality of care delivered to the patients (Chaudhry et al., 2006; Goldzweig, Towfigh, Maglione, & Shekelle, 2009; Kaushal, Shojania, & Bates, 2003; Walker et al., 2005; Graetz et al., 2014). Use of EHRs for health information exchange has also improved the care coordination between physicians (Graetz et al., 2014). This can reduce the number of duplicative tests, prevent readmissions, prevent medication errors, and reduce the cost of care (Frisse et al., 2012; Kaelber & Bates, 2007; Walker et al., 2005; Kern, Wilcox, Shapiro, Dhopeshwarkar, & Kaushal, 2012).

EHRs provide access to discrete and linkable clinical data (Kudyakov et al., 2012). Administrative databases lack clinical data granularity while EHRs can provide access to rich clinical data such as vital signs, laboratory reports, medications, and diagnosis (Weiner, Lyman, Murphy, & Weiner, 2007). This rich data can prove very useful in conducting clinical research on patients, diseases, therapies, and disease outcomes (Weiner et al., 2007). EHRs are more reliable for identifying various metrics. For example, administrative data definitions helped to identify 75% of diabetic patients while using the clinical data from EHRs helped to identify 97% of diabetic patients (Tang, Ralston, Arrigotti, Qureshi, & Graham, 2007). EHRs have transformed clinical practice by providing automated alerts and providing guidelines for evidence-based medicine and best practices (Paul et al., 2015). Patients treated at hospitals which have fully implemented EHRs had fewer overdosing errors and were more likely to receive guideline-recommended care (Enriquez et al., 2015). Use of EHRs in outpatient settings for patients with diabetes significantly reduced their number of emergency department visits and hospitalizations (Reed et al., 2013). The hospitals which are non-EHR adopters and serve mostly the poor patients have significantly lower performance on quality measures (Jha et al., 2009a).

Computerized physician order entry functionality of EHRs has helped to reduce the rate of serious medication errors (Bates et al., 1999; Shulman et al., 2005; Zlabek et al., 2011), number of laboratory tests and radiology examinations (Zlabek et al., 2011), and monthly transcription costs (Zlabek et al., 2011). Implementation of computerized physician order entry functionality of EHRs also significantly reduced the medication turn-around time, radiology procedure completion time, and laboratory result reporting times and eliminated all physician and nursing transcription errors (Mekhjian et al., 2002). It was also associated with significant decrease in charges per admission, bed charges, diagnostic test charges, and drug charges (Tierney et al., 1993). Clinical decision support system has shown to improve the quality of care provided in pneumonia patients (Mitchell et al., 2014). Use of EHRs while treating patients with coexisting chronic conditions showed improved patient outcomes and increased physician productivity (Dorr et al., 2006). Nurses in hospitals which have adopted basic EHRs have noted improved patient safety, quality of care, care coordination, and nursing care as compared to the nurses in hospitals which do not have EHRs (Kutney-Lee & Kelly, 2011).

Practices using EHRs showed improvement in their achievement of quality standards for diabetes and outcome standards for diabetes and diabetes care (Cebul, Love, Jain, & Hebert, 2011). The Veterans Health Administration hospitals have used EHRs and have shown an increase in the clinical quality (Jha, Perlin, Kizer, & Dudley, 2003; Perlin, 2006). EHRs have also shown the potential to reduce gaps in the quality of care provided to underserved patients (Jha et al., 2009a). Higher levels of EHR adoption are associated with increased process adherence and patient satisfaction (Adler-Milstein et al., 2015). More studies have shown increased patient satisfaction with the use of EHRs

(Freeman et al., 2009; Liu et al., 2013). Patients were satisfied with test result communications (Matheny et al., 2007; Ralston et al., 2007), secure messaging (Ralston et al., 2007), appointments (Ralston et al., 2007), and accurate information (Hassol et al., 2004).

Population Health Management and Electronic Health Records

In 2003, the Institute of Medicine (IOM) Committee on Data Standards for Patient Safety outlined eight core functionalities of the EHR system: health information and data, results management, order entry/management, decision support, electronic communication and connectivity, patient support, administrative processes, and reporting and population health management (IOM Committee on Data Standards for Patient Safety, 2003, p.7). This brought the focus on PHM through population health data reporting. The data extracted from the EHRs can help to determine the status of population health, identifying sick populations, targeting interventions to vulnerable populations, and monitoring the impact of interventions over time (Paul et al., 2015). This data can also help to identify risk factors in population and manage chronic conditions (Paul et al., 2015). EHRs can emerge as the hub of information exchange as the physicians document and upload diseases to the public health agencies to monitor diseases (Calman, Hauser, Lurio, Wu, & Pichardo, 2012).

Syndromic surveillance of populations through EHRs used in hospitals, clinics, etc. can help to detect outbreaks of diseases (Bordowitz, 2008). In the last few years, various epidemics, such as swine flu, Zika virus, Ebola virus, have threatened the health of people worldwide. Surveillance can help to identify initial cases and prevent epidemics. Louisiana Public Health Information Exchange (LaPHIE) was linked with the state surveillance data obtained from the EHRs (Herwehe et al., 2012). LaPHIE created alerts for providers when patients with HIV/AIDS did not receive HIV care for more than 12 months. It helped to reduce the number of missed opportunities to intervene with such individuals and thus leveraged the data to improve public health (Herwehe et al., 2012). Sidebottom et al. (2015) used EHRs as a tool for population health surveillance for cardiovascular risk factors in a rural community. They found that EHRs could produce reasonable risk factor prevalence estimate. They also noted that the use of EHRs for community assessment is more affordable than primary data collection. Using EHRs for PHM can also provide integrated patient data from various sources that the physicians can use to improve their decision making as well as identify patients that can benefit from care management. PHM interventions using EHRs have shown to increase screening rates, increase overall quality of care, and reduce disparities (Berkowitz et al., 2015). Since PHM focuses on managing conditions and maintaining the health of people, data collection through EHRs could prove to be a rich data source to identify at risk patients and intervene in a timely manner.

Enhancing registries through EHRs can help to identify vulnerable population groups and thus, to create and implement targeted interventions for these population groups (Bordowitz, 2008; Calman et al., 2012; Klompas et al., 2011). One study noted the importance of using EHR data for surveillance of asthma (Tomasallo et al., 2014). The EHR data had greater statistical power owing to the bigger sample size to detect associations especially in pediatric and ethnic populations (Tomasallo et al., 2014). The use of EHRs for surveillance and creating disease registries can help to research the associations as well as track adverse events (Savel & Foldy, 2012).

Previous studies have found EHRs to provide more complete, accurate, faster, and efficient laboratory data for public health surveillance as compared to the paper records (Dixon, Siegel, Oemig, & Grannis, 2013; Wurtz & Cameron, 2005; Centers for Disease Control and Prevention [CDC], 2008; Overhage, Grannis, & McDonald, 2008; Nguyen, Thorpe, Makki, & Mostashari, 2007). There was a decrease of 7.9 days in the reporting time of diseases (Overhage et al., 2008). The volume of cases reported increased greatly (Overhage et al., 2008; Nguyen et al., 2007). One study showed an increase of 76% in the reported Salmonella cases (Gluskin, Mavinkurve, & Varma, 2014). Another study showed an increase of 4.4 times in the number of cases reported (Overhage et al., 2008). This provides the public health agencies the opportunity to track more people and track them faster (Gluskin et al., 2014). As indicated by the HITECH Act, providers and hospitals are required to submit reportable electronic data to their public health agencies. However, according to the 2009 Council of State and Territorial Epidemiologists survey, only 27 states had the technological capacity for transmission of electronic laboratory records (CDC, 2009). This could pose a hindrance for the implementation of the PHM objectives of MU of EHRs.

Adoption and Implementation of Electronic Health Records

Various factors are associated with the adoption and implementation of EHRs. Hospitals delivering higher quality of care were more likely to have all clinical decision support functions and computerized physician order entry modules of EHRs and were also more likely to implement many of the MU criteria (Elnahal, Joynt, Bristol, & Jha, 2011). Hospitals which cater mostly to poor patients were associated with lower rates of EHR adoption especially for electronic medication lists, electronic discharge summaries, and clinical decision-support tools functionalities (Jha et al., 2009a). From 2008 to 2009, there was a modest increase in the hospitals that adopted EHRs, however, there was a growing gap between the adoption among large, private, and urban hospitals and adoption among small, public, and rural hospitals (Jha et al., 2010). The HITECH Act has played a large role in encouraging the use of EHRs to bridge the gap between high performing and low performing hospitals (Elnahal et al., 2011). A recent study showed that financial incentives and technical support systems through the HITECH Act have encouraged the office-based physicians to adopt and use EHRs for MU (Hsiao et al., 2013).

Barriers and Enablers of Adoption and Implementation of EHRs. Previous studies have found several environmental and organizational factors that are associated with the adoption of EHRs. Larger hospitals (Zhang et al., 2013; Burke, Wang, Wan, & Diana, 2002; Wang, Wan, Burke, Bazzoli, & Lin, 2005; Kazley & Ozcan, 2007; Furukawa, Raghu, Spaulding, & Vinze, 2008; Parente & Van Horn, 2006; Jha, DesRoches, Kralovec, & Joshi, 2010; Jha et al., 2009b; Diana, Harle, Huerta, Ford, & Menachemi, 2015; DesRoches et al., 2013), for-profit hospitals (Zhang et al., 2013; Furukawa et al., 2008; Taylor et al., 2005; Amarasingham et al., 2008; Diana et al., 2015), teaching hospitals (Kazley & Ozcan, 2007; Furukawa et al., 2008; Amarasingham et al., 2008; Jha et al., 2009b; DesRoches et al., 2013), urban hospitals (Burke et al., 2002; Kazley & Ozcan, 2007; Furukawa et al., 2008; Jha et al., 2010; Jha et al., 2009b;

DesRoches et al., 2013), and hospitals in competitive markets (Burke et al., 2002) are more likely to adopt EHRs. DesRoches et al. (2013) also noted that the hospitals that met Stage 1 of meaningful use criteria were likely to be large, teaching, private not-for-profit, and urban hospitals; and the hospitals that met Stage 2 of meaningful use criteria are more likely to be large, urban, non-for-profit, and teaching hospitals.

The savings associated with the use of EHRs may motivate the hospitals to adopt and implement EHRs. Hillestad et al. (2005) estimated that the effective implementation of EHRs could result in savings of $81 billion per year through improvement of health care efficiency and patient safety. Walker et al. (2005) estimated that the information exchange across providers, hospitals, public health agencies, and payers could result in savings of $77.8 billion annually. Hospitals may also adopt EHRs because of the domino effect associated with greater patient satisfaction with EHRs (Kazley, Diana, Ford, & Menachemi, 2012). The increased patient satisfaction among such hospitals may result in organizational benefits other than financial performance (Chaudhry et al., 2006; Kern et al., 2012) or clinical quality (Deckelbaum et al., 2009; Kazley & Ozcan, 2008; McCullough, Casey, Moscovice, & Prasad, 2010). Adoption of EHRs could help the hospital to gain repeat patients, increase the likelihood of being recommended to another patient, and to strengthen its position as a brand in the market (Kazley et al., 2012).

Lack of financial resources was cited as the greatest barrier to adoption and implementation of EHRs. Financial resources are important in facilitating successful adoption of EHRs (Nakamura, Ferris, DesRoches, & Jha, 2010; Ginn, Shen, & Moseley, 2011; Shen & Ginn, 2012; Gabriel, Jones, Samy, & King, 2014). Hospitals with a higher total margin were more likely to adopt EHRs (Shen & Ginn, 2012). Hospitals with lower liquidity (Ginn et al., 2011), higher asset turnover (Ginn et al., 2011; Shen & Ginn, 2012), and higher equity multiplier (Shen & Ginn, 2012) were in a poorer position to adopt EHRs. Hospitals which serve mostly the poor populations expressed significant concerns about capital to purchase EHR and lack of support in the future to maintain the EHR system (Jha et al., 2009a). Other studies have also noted that the initial costs (Miller & Sim, 2004; Simon et al., 2007; Jha et al., 2009b; Abramson et al., 2012), maintenance costs (Simon et al., 2007; Jha et al., 2009b; Abramson et al., 2012), and uncertain financial benefits (Miller & Sim, 2004) have deterred the hospitals from adopting EHRs. Additionally, the financial burden falls on the physicians and hospitals while the benefits and savings are reaped by the patients and the payers (Hillestad et al., 2005). This could discourage physicians and hospitals to use EHRs. Although the EHRs incentives programs were designed to financially aid the hospitals, physicians can overcome the financial barriers but would continue to face technical problems (Xierali, Phillips, Green, Bazemore, & Puffer, 2013).

Several other factors are identified through the literature as barriers to adoption of EHRs. Physician resistance (Simon et al., 2007), physician time investment (Miller & Sim, 2004), lack of technical support (Jha et al., 2009b; Simon et al., 2007; Abramson et al., 2012), lack of resources for training staff (Abramson et al., 2012), lack of clear policies or standards (Abramson et al., 2012), loss of productivity (Simon et al., 2007), privacy concerns (Simon et al., 2007), and inadequate electronic data exchange (Miller & Sim, 2004; Adler-Milstein, McAfee, Bates, & Jha, 2008) are other barriers to adoption of EHRs. Initial implementation of EHRs has proven challenging. The length of stay and time to doctor increased during the initial EHR implementation (Kennebeck, Timm, Farrell, & Spooner, 2012) which could further discourage the implementation of EHRs.

Physician characteristics were also identified as barriers to adoption of EHRs. Older family physicians, female family physicians, international medical graduates, physicians in solo practices, physicians in health professional shortage area, and physicians in underserved areas were less likely to adopt EHRs (Xierali et al., 2013). The physician could also choose not to adopt EHRs for their self-interest. Kaelber, Waheed, Einstadter, Love, & Cebul (2013) noted that there is lesser health information exchange among privately insured patients. Using EHRs for health information exchange has helped to avoid duplicative tests and unnecessary hospitalizations which may not serve in the physician's interest, thus discouraging the adoption of EHRs (Kaelber et al., 2013).

HITECH Act and EHRs Incentive Programs

The Health Information Technology for Economic and Clinical Health (HITECH) Act was enacted as a part of the American Recovery and Reinvestment Act (ARRA) of 2009. The HITECH Act was signed into law on February 17, 2009 in order to promote the adoption and meaningful use (MU) of health information technology (U.S. DHHS, n.d.). A key component of the health information technology is the EHR technology. The HITECH Act intended to achieve the MU of EHRs through the adoption and implementation of EHRs. MU is defined as "using certified EHR technology: to improve quality, safety, efficiency, and reduce health disparities; engage patients and family; improve care coordination, and population and public health; and maintain privacy and security of patient health information" (HealthIT.gov, 2015, February 6). Complying with

MU may result in improved clinical and population health outcomes, increased transparency and efficiency, empowered individuals, and robust data on health systems (HealthIT.gov, 2015, February 6).

The ARRA Act of 2009 amended the Title XVIII and XIX of the Social Security Act to allow the Centers for Medicare and Medicaid Services (CMS) to set up Electronic Health Records Incentive Programs (CMS, 2016, November 22; HealthIT.gov, 2013a, January 15). About $30 billion were allocated in direct incentives through the EHRs incentive programs. These EHRs Incentive Programs were set up in order to promote the adoption and MU of EHRs (CMS, 2016, November 22). Through these programs, eligible professionals, eligible hospitals, eligible critical access hospitals, and Medicare Advantage Organizations could receive incentive payments for demonstrating MU (CMS, 2016, November 22). The following hospitals are considered as eligible hospitals: 1. Subsection (d) hospitals in the 50 U.S. States or DC that are paid based on inpatient prospective payment system, 2. Critical access hospitals (CAH), or 3. Medicare-Advantage affiliated hospitals (CMS, 2016. January 12). If an eligible hospital fails to demonstrate of MU of EHRs, they will receive payment adjustments from the CMS (Medicare and Medicaid Programs Electronic Health Record Incentive Program-Stage 2, 2012). Eligible hospitals which fail to demonstrate MU of EHRs can claim hardship exceptions to payment adjustments if they fall into the following three categories: 1. Lack of availability of internet access or barriers to obtaining IT infrastructure, 2. A time limited exception for newly practicing hospitals, and 3. Unforeseen circumstances such as natural disasters (Medicare and Medicaid Programs Electronic Health Record Incentive Program-Stage 2, 2012, September 4). Thus, CMS rewards those eligible hospitals which demonstrate MU of EHRs while penalizing those that don't demonstrate MU of EHRs.

During the HITECH law enactment, it was proposed that MU would be achieved in three stages (CMS, 2012, August). The first implementation of Stage 1 was in 2011 (CMS, 2012, August). CMS established a timeline which required hospitals to progress to Stage 2 after demonstrating Stage 1 of MU of EHRs for two years (CMS, 2012, August). Thus, the hospitals which demonstrated Stage 1 of MU of EHRs in 2011 were required to demonstrate Stage 2 of MU of EHRs in 2013. However, CMS delayed the onset of Stage 2 to 2014 (CMS, 2012, August). Consequently, the earliest implementation of Stage 2 was in 2014. Further, according to the timeline established by the CMS, hospitals were required to progress to Stage 3 of MU of EHRs after demonstrating two years of Stage 2 of MU of EHRs. Thus, the hospitals which demonstrated Stage 2 of MU of EHRs in 2014 would be required to demonstrate Stage 3 of MU of EHRs in 2016. However, CMS delayed the onset of Stage 3 to 2017. Thus, the earliest implementation of Stage 3 would be in 2017 (Medicare and Medicaid Programs; Electronic Health Record Incentive Program—Stage 3 and Modifications to Meaningful Use in 2015 through 2017, 2015, October 16). This timeline shows the stage of MU of EHRs for early adopters of EHRs who started implementation of MU of EHRs in 2011. There are hospitals which have started the implementation of MU of EHRs in the consequent years. These hospitals also follow the established rule of demonstrating a stage of MU of EHRs for two years and then progressing to the next stage.

During the Stage 1, data would be captured and shared through EHRs. The Stage 2 would help to advance clinical processes and Stage 3 would help to improve outcomes

(HealthIT.gov, 2015, February 6). The goals of these three stages are as follows (HealthIT.gov, 2013b, January 15):

Stage 1:

- Use EHRs to capture health information in a standardized format.
- Use the information obtained from EHRs to track key clinical conditions
- Use EHRs to communicate the information obtained on clinical conditions through EHRs to coordinate care
- Use EHRs to report clinical quality measures and public health information
- Use information from EHRs to engage patients and their families in care processes

Stage 2:

- Use EHRs for more rigorous health information exchange (HIE)
- Use EHRs for e-prescribing and incorporating lab results
- Use EHRs to transmit patient care summary across multiple healthcare settings
- Use EHRs for more patient-controlled data

Stage 3:

- Use the data from EHRs to improve quality, safety, and efficiency; thus, leading to better health outcomes
- Use EHRs to obtain decision support for high-priority conditions
- Use EHRs to provide patients with access to self-management tools
- Use EHRs to access detailed patient data through patient-centered HIE
- Use EHRs to improve population health

Although PHM was not an explicit goal stated for Stage 1 and Stage 2, PHM objectives are included in both Stage 1 and Stage 2. Each stage has a well-defined set of core and menu objectives. The core objectives are mandatory and all eligible hospitals must meet the core objectives to demonstrate MU. The menu objectives are a set of objectives and eligible hospitals must meet a pre-determined number of objectives from this list. In order to demonstrate MU, eligible hospitals need to meet both, their core and menu, objectives. Under the Stage 1 criteria, eligible hospitals have to meet 14 core objectives and any five menu objectives from a list of ten. The core objectives for Stage 1 are as follows (CMS, 2010):

1. Use computerized provider order entry (CPOE) for medication orders directly entered by any licensed healthcare professional who can enter orders into the medical record per state, local, and professional guidelines
2. Implement drug-drug and drug-allergy interaction checks
3. Record demographic information: preferred language, gender, race, ethnicity, date of birth, and date and preliminary cause of death in the event of mortality in the eligible hospital
4. Maintain up-to-date problem list of current and active diagnoses
5. Maintain active medication list
6. Maintain active medication allergy list
7. Record and chart vital signs: height, weight, blood pressure, calculate and display BMI, plot and display growth charts for children 2-20 years, including BMI
8. Record smoking status for patients 13 years old or older

9. Implement one clinical decision support rule and the ability to track compliance with the rule
10. Report clinical quality measures to CMS or the States
11. Provide patients with an electronic copy of their health information (including diagnostic test results, problem list, medication lists, medication allergies, discharge summary, procedures), upon request
12. Provide patients with an electronic copy of their discharge instructions at time of discharge, upon request
13. Capability to exchange key clinical information (ex: problem list, medication list, medication allergies, diagnostic test results), among providers of care and patient authorized entities electronically
14. Protect electronic health information created or maintained by certified EHR technology through the implementation of appropriate technical capabilities

The menu objectives for Stage 1 are as follows (CMS, 2010):

1. Implement drug-formulary checks
2. Record advance directives for patients 65 years old or older
3. Incorporate clinical lab-test results into certified EHR technology as structured data
4. Generate lists of patients by specific conditions to use for quality improvement, reduction of disparities, research or outreach
5. Use certified EHR technology to identify patient specific education resources and provide those resources to the patient, if appropriate

6. The eligible hospital who receives a patient from another setting of care or provider of care or believes an encounter is relevant should perform medication reconciliation
7. The eligible hospital who receives a patient from another setting of care or provider of care or refers their patient to another provider of care should provide a summary of care record for each transition of care or referral
8. Capability to submit electronic data to immunization registries or Immunization Information Systems and actual submission in accordance with applicable law and practice
9. Capability to submit electronic data on reportable (as required by state or local law) lab results to public health agencies and actual submission in accordance with applicable law and practice
10. Capability to submit electronic syndromic surveillance data to public health agencies and actual submission in accordance with applicable law and practice

The Stage 1 criteria mentioned above which were first set in 2011were revised subsequently in 2013 and 2014. All eligible hospitals had to demonstrate at least one of the three PHM objectives which are included in the menu objectives (Menu objective 8, 9, and 10 as listed above) (CMS, 2013 May). Most of the Stage 1 core and menu objectives were retained as the Stage 2 core objectives. The core objective of “capability to exchange key clinical information (ex: problem list, medication list, medication allergies, diagnostic test results), among providers of care and patient authorized entities electronically” was removed (CMS, 2013 May). The core objective of “record and chart vital signs: height, weight, blood pressure, calculate and display BMI, plot and display growth charts for children 2-20 years, including BMI" was edited to increase the age limit for recording blood pressure in patients to age 3 and remove the age limit requirement for height and weight (CMS, 2013 May). The core objective of "use computerized provider order entry (CPOE) for medication orders directly entered by any licensed healthcare professional who can enter orders into the medical record per state, local, and professional guidelines" was modified to give an alternative objective of "record more than 30 percent of medication orders created by the authorized providers of the eligible hospital's during the EHR reporting period using CPOE"; and the eligible hospitals were given a choice to implement either the original measure or the alternate one (CMS, 2013 May). The core objectives of "provide patients with an electronic copy of their health information (including diagnostic test results, problem list, medication lists, medication allergies, discharge summary, procedures), upon request" and "provide patients with an electronic copy of their discharge instructions at time of discharge, upon request" were replaced with "provide patients the ability to view online, download and transmit information about a hospital admission" in 2014 (CMS, 2014, March). To demonstrate MU under the Stage 2 criteria, eligible hospitals were required to meet 16 core objectives and three menu objectives from a list of six objectives. The core objectives for Stage 2 are as follows (CMS, 2012, August):

1. Use computerized provider order entry (CPOE) for medication, laboratory and radiology orders
2. Record demographic information
3. Record and chart changes in vital signs
4. Record smoking status for patients 13 years old or older

5. Use clinical decision support to improve performance on high-priority health conditions
6. Provide patients the ability to view online, download and transmit their health information within 36 hours after discharge
7. Protect electronic health information created or maintained by the Certified EHR Technology (CEHRT)
8. Incorporate clinical lab-test results into Certified EHR Technology
9. Generate lists of patients by specific conditions to use for quality improvement, reduction of disparities, research, or outreach
10. Use certified EHR technology to identify patient-specific education resources and provide those resources to the patient if appropriate
11. Perform medication reconciliation
12. Provide summary of care record for each transition of care or referral
13. Submit electronic data to immunization registries
14. Submit electronic data on reportable lab results to public health agencies
15. Submit electronic syndromic surveillance data to public health agencies
16. Automatically track medications with an electronic medication administration record (eMAR)

The menu objectives for Stage 2 are as follows (CMS, 2012, August):

1. Record whether a patient 65 years old or older has an advance directive
2. Record electronic notes in patient records
3. Imaging results accessible through CEHRT
4. Record patient family health history

5. Generate and transmit permissible discharge prescriptions electronically (eRx)
6. Provide structured electronic lab results to ambulatory providers

Both Stage 1 and Stage 2, include three PHM objectives (CMS, 2014 July). Stage 1 has these PHM objectives as menu objectives: a). capability to submit electronic data to immunization registries or Immunization Information Systems and actual submission in accordance with applicable law and practice, b). capability to submit electronic data on reportable (as required by state or local law) lab results to public health agencies and actual submission in accordance with applicable law and practice, and c). capability to submit electronic syndromic surveillance data to public health agencies and actual submission in accordance with applicable law and practice (CMS, 2014 July). Even though the eligible hospitals in Stage 1 are given an option of selecting five out of ten specified menu objectives, one of the selected objectives should be a PHM objective (CMS, 2014 July). Stage 2 revises these objectives and includes them as core objectives: a. submit electronic data to immunization registries, b. submit electronic data on reportable laboratory results to public health agencies, and c. submit electronic syndromic surveillance data to public health agencies (CMS, 2014 July). A hospital can claim exclusion and is exempt from meeting the three PHM objectives if its public health department is unable to support connectivity (DesRoches et al., 2013; Medicare and Medicaid Programs Electronic Health Record Incentive Program-Stage 2, 2012).

Impact of EHRs Incentive Programs on Hospitals

The EHRs incentive programs have created a mixed effect for hospitals (Mirani & Harpalani, 2014). While more hospitals are adopting EHRs, hospitals have adopted only the basic EHR functionalities which could enable them to receive incentives. Mirani & Harpalani (2014) suggest that these adopters have used the program's rules to their short-term advantage instead of the long-term implementation and use of EHRs.

By April 2013, about 3800 hospitals had received incentive payments through the EHRs incentive programs (Furukawa, Patel, Charles, Swain, & Mostashari, 2013). The adoption of EHR systems by non-federal acute care hospitals has increased steadily since the HITECH Act (Henry, Pylypchuk, Searcy, & Patel, 2016, May). Basic EHR adoption (defined as use of all functionalities of EHR by at least one unit in the hospital) increased from 7.8 percent in 2008 to 43.8 percent in 2015; comprehensive EHR adoption (defined as use of all functionalities of EHR by all units of the hospital) increased from 1.6 percent in 2008 to 40.0 percent in 2015 (Henry et al., 2016, May).

In 2014, 58 percent of the eligible hospitals at Stage 1 reported on their capability to submit electronic data to immunization registries and 88 percent of the eligible hospitals at Stage 2 submitted electronic data to immunization registries (Heisey-Grove, Chaput, & Daniel, 2015, March). In 2014, 14 percent of the eligible hospitals at Stage 1 reported on their capability to submit electronic data on reportable laboratory results to public health agencies and 85 percent of the eligible hospitals at Stage 2 submitted electronic data on reportable laboratory results to public health agencies (Heisey-Grove et al., 2015, March). In 2014, 23 percent of the eligible hospitals at Stage 1 reported on their capability to submit electronic syndromic surveillance data to public health agencies and

75 percent of eligible hospitals at Stage 2 submitted electronic syndromic surveillance data to public health agencies (Heisey-Grove et al., 2015, March). No study has been conducted to identify the factors associated with the MU of EHRs for PHM in U.S. acute care hospitals

Summary of the Chapter

This chapter presented an overview of population health management (PHM) and electronic health records (EHRs). It discussed the importance of EHRs as proven from the literature and the use of EHRs for PHM. It identified factors associated with adoption and implementation of EHRs and the barriers to adoption and implementation of EHRs. It described the HITECH Act and EHRs incentive programs in detail. It listed all the objectives of meaningful use of EHRs and identified the PHM objectives. The literature review indicated that some functionalities of EHRs such as computerized physician order entry and clinical decision support system have been used and studied extensively but the literature on use of EHRs for PHM is very scarce. Although there is a great shift of attitude of payers towards PHM, the literature fails to provide any evidence on the extent of MU of EHRs for PHM. As MU approaches Stage 3 and the healthcare system moves towards value-based models, it becomes important to investigate the factors that are associated with the use of EHRs for PHM. This could inform policymakers and practitioners and help to take necessary steps towards PHM.

Chapter three presents the theoretical framework used to conceptualize this study. It describes the conceptual model and states the research hypotheses based on the conceptual framework.

CHAPTER THREE: THEORETICAL BACKGROUND

This chapter includes two sections. The main theme of the first section is the adoption of innovation in organizations. This section provides an overview including definitions and the types of innovation, and discusses the theoretical perspectives of adoption of innovation in organizations. The second section focuses on the theoretical framework that is used to address the research questions of this study. This section describes the theoretical background, the conceptual framework based on the described theory, and discusses the key constructs and hypotheses to be tested.

Part I: Innovation

Overview of Innovation

There are several definitions of innovation in the literature. Innovation has been defined as

> “the adoption of an idea or behavior-whether a product, device, system, process, policy, program, or service-that is new to the adopting organization” (Damanpour, 1988, p.546).

> “production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems. It is both a process and an outcome” (Crossan & Apaydin, 2010, p. 1155).

Innovation is considered as a way to change the organization, either as a reaction to the changing environment or as a preemptive action to influence the environment or as a response to technological or market challenges (Damapour, 1988; Damanpour & Evan, 1984; Hage, 1999). An organization's survival and success depends on the organization's ability to maintain equilibrium with the environment, and the adoption of innovation is a means to attain that equilibrium (Lawrence & Lorsch, 1967). Organizations continuously adopt innovations to suit their dynamic environment (Damanpour, 1988). Innovation helps organizations to maintain a competitive advantage (Porter, 1980).

Researchers have categorized innovation into two types: administrative innovation and technical innovation (Damanpour 1988; Daft, 1978; Evan & Black, 1967). Administrative innovations are related to the "organizational structure and administrative processes, that is, they are indirectly related to the basic work activities of the organization and more directly related to its management" (Damanpour, 1988, p. 548). Technical innovations are related to the "products, services, and production process technology, that is, they are related to the basic work activity of the organization" (Damanpour, 1988, p. 548). Technical innovations can be either product or process innovations (Damanpour, 1988) Product innovations are "new products or services introduced to meet an external user or market need" (Damanpour, 1991, p. 561). Process innovations are "new elements introduced into and organization's production or service operations used to produce a product or render a service" (Damanpour, 1991, p. 561).

The Organisation for Economic Co-operation and Development [OECD] (2005), however, classifies innovation into four categories: product innovation, process innovation, marketing innovation, and organizational innovation. Product and process innovations are also referred to as technological innovations, while marketing and organizational innovations are also referred to as non-technological innovations. OECD (2005) defined organizational innovation as the “introduction of new organizational methods for business management in the workplace and/or in the relationship between a company and external agents”. Camisón and Villar-López (2014) noted that organizational innovation promotes technological capabilities of an organization and facilitates technological innovation.

It is necessary to differentiate between these types of innovation because the factors affecting the adoption of these innovations are different (Damanpour, 1988; Daft, 1978; Evan & Black, 1967). The decision-making process is different for these innovations as well (Daft, 1978). A low-cost business strategy can be implemented to reducing costs through process innovation while a differentiation strategy can be implemented through product innovation (Porter 1980).

Adoption of Innovation

Stages of Adoption of Innovation. The adoption of innovation is a continuous process. Previous studies have conceptualized the adoption of innovation in two stages: initiation and implementation (Duncan, 1976; Rogers, 2010; Zaltman, Duncan & Holbek, 1973). These two stages are conceptualized as such because they have distinct processes and are influenced differently by organizational factors. The initiation stage is comprised of identifying a problem, gathering information related to the problem, evaluating the information, and deciding whether or not to adopt the innovation (Rogers, 2010; Zaltman et al., 1973). The implementation stage is comprised of using the innovation initially and then maintaining the continuous use of innovation in the organization (Rogers, 2010;

Zaltman et al., 1973). The ambidextrous model as proposed by Duncan (1976) suggests that high structural complexity, low formalization, and low centralization in an organization facilitate the initiation stage of adoption of innovation while the opposite conditions facilitate the implementation stage of adoption of innovation. Daft (1978) suggested that technological innovations can be implemented successfully in organizations that have an organic structure while administrative innovations can be implemented successfully in mechanistic or bureaucratic organizations.

Factors Affecting the Adoption of Innovation. Various intra-organizational and extra-organizational factors may impede or facilitate the implementation of innovation (Barnett, Vasileiou, Djemil, Brooks, & Young, 2011). Organizational climate and financial resources can affect the implementation of innovation in an organization. Klein & Sorra (1996) proposed that the organization’s climate for implementation of an innovation is determined by its employees’ perceptions of using the innovation. If the employees are encouraged and rewarded for their use of the innovation, the organizational climate is stronger for the implementation of the innovation. Further, implementation of innovation often requires training program for the employees, and continual support as the user pool grows. The costs for training and support can make the implementation of innovation expensive (Klein & Knight, 2005). Thus, the financial resources of the organization can affect the implementation of innovation in an organization.

Organizational factors such as size and complexity are associated with adoption of innovation (Damapour 1996; Baldridge & Burnham, 1975). Larger size creates problems of coordination, control, and management which require innovative approach.

This stimulates the adoption of innovations to handle such problems (Baldridge & Burnham, 1975). Larger organizations have more complex structure with more role differentiation. This differentiation helps to bring expertise, support, and specialized resources into the organizations, thus facilitating the adoption of innovation (Baldridge & Burnham, 1975). Environmental factors such as uncertainty (Damanpour, 1996; Baldridge & Burnham, 1975), dynamism of the environment (Baldridge & Burnham, 1975), and market competition (Utterback, 1974) are also associated with the adoption of innovation. Factors associated with adoption of technological innovation are size of the organization, specialized and functionally differentiated organizational structure, and market competition while the factor associated with the adoption of administrative innovation is size of the organization (Kimberly & Evanisko, 1981). These studies establish the importance of organizational and environmental factors in an organization's strategic behavior for adoption of innovation.

This study focuses on the implementation stage of the adoption of innovation. EHRs are technological innovations. An organization's strategic behavior to implement MU of EHRs for PHM may be associated with the organizational and environmental factors as brought forth by the studies discussed above.

Part II: Theoretical Framework

The following section describes the theoretical framework and the conceptualization process to answer the research questions of this study:

1. What are the organizational and environmental factors associated with the implementation of the PHM objectives of MU of EHRs in acute care hospitals in the U.S.?
2. What are the organizational and environmental factors associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S.?

This study used the resource dependency theory to develop a conceptual framework to address these research questions.

Overview of the Resource Dependency Theory

Barnard was the first to discuss the relationship between an organization and the external environment in “The Functions of the Executive” in 1938 (Barnard, 1938). He suggested that despite the weaknesses of an organization, the cause of instability for an organization lies in the external forces exerted by the environment (Barnard, 1938). He proposed that “the survival of an organization depends upon the maintenance of an equilibrium of complex character in a continuously fluctuating environment of physical, biological, and social materials, elements, and forces which calls for readjustment of processes internal to the organization” (Barnard, 1938, p.6). Thompson (1967) proposed that an organization’s dependence on an element in the environment increases if the element can provide the organization with the necessary resources; on the other hand, if other elements in the environment can provide the necessary resource to the organization then the organization's dependence on one element in the environment decreases. Jacobs (1974) suggested similarly, that organizations are controlled through exchange relationships with their environment and organizations need to adapt to their environment to survive. However, Mindlin and Aldrich (1975) proposed that the number of suppliers is not as important as the importance of each supplier to the organization depending on it for resources. Benson (1975) focused on inter-organizational relationships and explained that interdependence between organizations is not the only way to acquire resources and power. Organizations are dependent on the environment and an organization which maintains links with the environment are more likely to be resourceful and powerful within their organizational network (Benson, 1975). Cook (1977) argued that organizations exert dominance by gaining control over the flow of resources within organizational networks.

Pfeffer and Salancik (1978) suggested that organizations survive till they are effective; an organization's ability to be effective comes from the management of the demands of the groups on which the organization is dependent on for resources or support. No organization is "self-contained"; an organization needs to acquire and maintain resources to survive and these resources are obtained from other organizations which are present in a given environment (Pfeffer & Salancik, 1978). Based on this idea, Pfeffer and Salancik (1978) proposed the resource dependency theory. Organizations cannot generate all resources required by them internally. Hence, organizations in an environment depend on each other for resources for their survival. The resource dependency theory proposed that organizations may need to alter their strategic behavior to acquire the necessary resources from the environment. “According to the resource dependence perspective, firms do not merely respond to external constraints and control through compliance to environmental demands. Rather, a variety of strategies may be undertaken to somehow alter the situation confronting the organization to make compliance less necessary” (Pfeffer, 1982, pp. 197). The resource dependency theory gives control to the environment as it "denies the validity of the conceptualization of organizations as self-directed, autonomous actors pursuing their own ends and instead argues that organizations are other directed, involved in a constant struggle for autonomy and discretion, [and] confronted with constraint and external control" (Pfeffer and Salancik, 1978, p. 257). The advantage of resource dependence perspective is the ability to maintain autonomy over decision-making process and the flexibility to adapt as new contingencies arise (Oliver, 1991).

The resource dependence perspective characterizes the links among organizations as power relationships based on exchanges of resources (Ulrich & Barney, 1984). This perspective makes three assumptions to explain how organizations acquire power. The first assumption is that organizations are comprised of internal and external coalitions; these coalitions are formed to influence and control behavior and they arise from social exchanges (Pfeffer & Salancik, 1978). The second assumption is that environment contains scarce and valuable resources necessary for the survival of the organization and the environment poses a threat of uncertainty to these organizations to acquire their resources (Pfeffer, 1978). The third assumption is that organizations work towards two objectives within their environment: 1. to minimize their own dependence on other organizations by controlling resources, and 2. to maximize the dependence of other organizations on themselves by controlling resources (Pfeffer & Pfeffer, 1981). The three key constructs of resource dependency theory are munificence, uncertainty, and interdependence.

Munificence refers to the availability and the accessibility of necessary resources from the internal and external environment (Pfeffer & Salancik, 1978). The resources needed by an organization may be plentiful or scarce in the environment. If the resources are plentiful then organization's dependence on the environment decreases, but if the resources are scarce then the organization's dependence on the environment increases. Abundant resources allow more flexibility in terms of operations and services (Menachemi et al., 2011). An organization may alter its behavior depending on the resources available in the environment. For example, if the survival of a hospital is dependent on specialists, rural hospitals which generally have a lack of specialists (which is resource scarcity in their environment) would not remain viable. So, a rural hospital may implement the use of health information technology such as telehealth to bring access to specialists in their hospital thus nurturing their survival in the market (Yeager et al., 2014).

Uncertainty refers to the variability and the complexity in acquiring resources from the environment (Pfeffer & Salancik, 1978). Organizations in dynamic and complex environments face the highest amount of uncertainty in decision (Duncan, 1972). The environment is dynamic due to the organizations entering and exiting from an environment. This creates a competitive market where all the organizations in that environment are competing for the limited pool of resources (Pfeffer & Salancik, 1978). This may reduce the amount of resources available for the organizations in this environment. An organization may need to alter its behavior to be less dependent on the environment for its resources or to increase their control on resources available in the environment (Menachemi et al., 2011).

Interdependence refers to the dependency of organizations on one another to secure resources and survive (Pfeffer & Salancik, 1978). An organization may alter its behavior to develop relationships with other organizations in the environment to increase the dependence of other organizations on themselves or to reduce their dependence on other organizations in the environment (Ulrich & Barney, 1984). An organization may also change their structure and behavior to accommodate the needs of the other organizations on which it is dependent to maintain a steady flow of resources. An organization may enter interdependent relationships with other organizations to gain power in the market. Organizational power may help the organizations secure the necessary resources from the environment. If the resource is scarce or specialized and there are limited number of suppliers for this resource in the environment, the power shifts to the suppliers making the organizations more compliant (Weech-Maldonado et al., 2009).

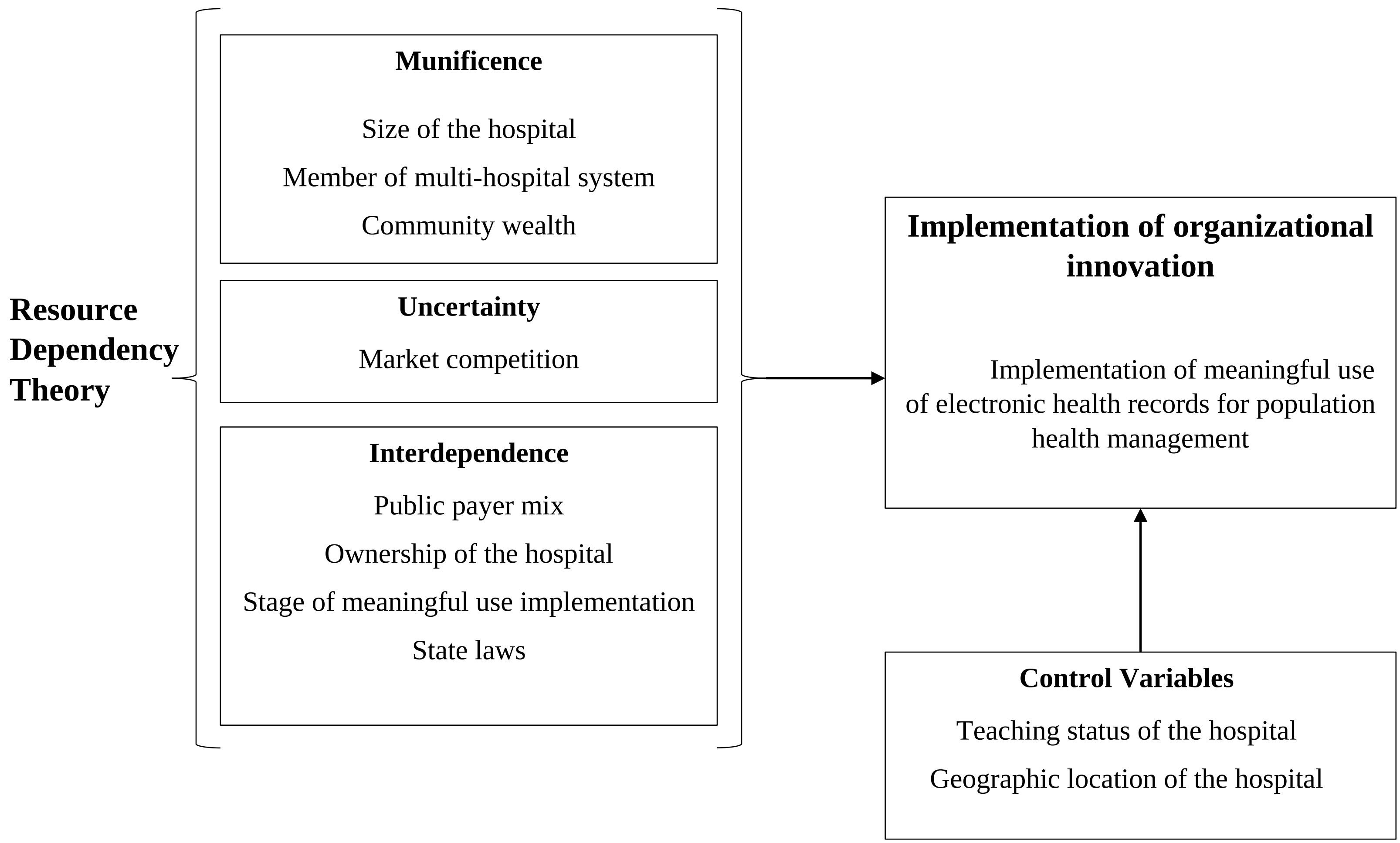
Development of the Conceptual Framework

The conceptual framework for this study was developed using the resource dependency perspective. This study focuses on the strategic behavior of acute care hospitals in the U.S. The unit of analysis for this study is an individual acute care hospital in the U.S. An acute care hospital is defined as a general medical and surgical care hospital which "provides acute care to patients in medical and surgical units on the basis of physicians' orders and approved nursing care plans" (American Hospital Association, 2014, p. 119). This study assumes that acute care hospitals in the U.S. are dependent on their environment for resources; and as posited by the resource dependency theory, they alter their strategic behavior according to the available resources to remain competitive and survive in the market.

The market in which the acute care hospital exists is its environment. An acute care hospital depends on this environment for resources necessary for its survival. Physicians, nurses, other healthcare professionals, patients, and medical equipment are few examples of resources that are obtained from the environment. These resources may be abundant or scarce in the environment. The amount of these resources may continuously change depending on the market conditions. Further, an acute care hospital may be dependent on other organizations to secure these resources. For example, an acute care hospital may be dependent on third party payers such as government (for example, Centers for Medicare and Medicaid Services), insurance companies or companies that sell medical equipment. This makes the environment of the acute care hospital dynamic and complex. Consequently, acute care hospitals may strategize to maximize their control on resources and minimize their dependence on other organizations.

As discussed previously in chapter 2, implementation of MU of EHRs for PHM could be a strategy used by the acute care hospitals to gain control over resources and to minimize dependency on other organizations, thus making the acute care hospital viable in a competitive and dynamic market. The key behavioral construct in this study is the implementation of organizational innovation which is operationalized as the implementation of MU of EHRs for PHM. The causal constructs are based on the resource dependence theory's three key constructs of munificence, uncertainty, and interdependence. Munificence is defined as the amount of resources available in the organization's internal and external environment. Munificence is operationalized as the size of the hospital, membership of multi-hospital system, and the community wealth of the area in which the hospital is located. Uncertainty is defined as the degree of dynamic environment of the hospital. Uncertainty is operationalized as the degree of market competition for the hospital. Interdependence is defined as the dependence of hospital on other stakeholders. Interdependence is operationalized as the public payer mix of the hospital, ownership of the hospital, stage of implementation of MU of EHRs, and the state regulatory environment of the hospital. Figure 1 illustrates the conceptual framework that is used to derive the hypotheses related to this study's research questions.

Figure 1: Conceptual Framework



Research Hypotheses

This part of the chapter describes the operationalization of the three key constructs of the resource dependency theory: munificence, uncertainty, and interdependence. The conceptual framework developed above is used to elaborate the research hypotheses for this study.

Munificence. The availability or the scarcity of resources in the environment can decrease or increase the organization's dependence on the environment. Securing resources, from external or internal environment, can help to reduce the organization's dependence on the environment. Organizations strategize to control necessary resources and reduce their dependence on the environment to stay viable in the market. In this study, munificence is operationalized as the size of the organization, membership of multi-hospital system, and the community wealth in the environment.

Organizational capacity can influence the strategic behavior of the organization. If the organization has abundant resources internally, its dependence on the environment decreases (Banaszak-Holl, Zinn, & Mor, 1996). The greater amount of resources also enables the organization to accommodate environmental needs and demands (Banaszak-Holl et al., 1996; Alexander & Morrisey, 1989; Zinn, Mor, Castle, Intrator, & Brannon, 1999; Greening & Gray, 1994; Fareed & Mick, 2011). These internal resources also provide the organization flexibility to add new functions or services (Alexander & Morrisey, 1989). Organizational capacity has been measured as the size of the organization (Banaszak-Holl et al., 1996). Previous studies that have used the resource dependency perspective have also used organizational size to operationalize munificence

(Banaszak-Holl et al., 1996; Zinn et al., 1999; Zinn, Weech, & Brannon, 1998; Kim & Thompson, 2012; Kazley & Ozcan, 2007). Organizational size is also associated with organizational power (Kim & Thompson, 2012; Kazley & Ozcan, 2007). Larger organizations may have more financial and human resources giving them more power (Kazley & Ozcan, 2007). This may enable the organizations to negotiate with their suppliers (Hatch, 1997; Kazley & Ozcan, 2007), gain more resources from the environment (Lucas et al., 2005; Zinn, Proenca, & Rosko, 1997), and control resources in the environment (Hatch, 1997; Lucas et al., 2005; Zinn et al., 1997). This suggests that larger acute care hospitals may have more financial and human resources to implement PHM objectives of MU of EHRs. These financial and human resources may also enable the hospital to create training programs and reward programs to incentivize their staff to use EHRs. Larger size of the hospital may thus allow the hospital to have more flexibility to implement MU of EHRs for PHM. Owing to their abundance of resources, it is also possible that larger hospitals have higher level of MU of EHRs for PHM. Previous studies have also noted that larger organizations are more likely to adopt innovations (Kaluzny, Veney, & Gentry, 1974; Banaszak-Holl et al., 1996). Larger organizations are also more likely to adopt EHRs (Zhang et al., 2013; Burke et al., 2002; Wang et al., 2005; Kazley & Ozcan, 2007; Furukawa et al., 2008; Parente & Van Horn, 2006; Jha et al., 2010; Jha et al., 2009b; Diana et al., 2015; DesRoches et al., 2013).

H1a: All else being equal, larger acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to smaller acute care hospitals.

H1b: All else being equal, larger acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to smaller acute care hospitals.

A multi-hospital system is defined as “two or more hospitals owned, leased, sponsored, or contract managed by a central organization” (American Hospital Association, 2014). In a multi-hospital system, the organizational control shifts from the individual hospital to the central headquarters of the system (Alexander & Fennell, 1986), and the ultimate decision-making power lies with the central headquarters of the organization or the parent organization (Mintzberg, 1979). The central headquarters develop policy and strategic direction for all the hospitals within their multi-hospital system (Alexander et al., 1986). The concentration of power at the central headquarters level can increase standardization, coordination, and central decision-making which may increase efficiency and performance of the hospitals within their system (Weill & Ross, 2004; Chan & Reich, 2007). Further, the central headquarters hold control over the resources within their system and have the power to reallocate these resources as necessary (Alexander et al., 1986). For example, a hospital may allocate financial resources from a profitable hospital to an unprofitable hospital to make capital improvements (Alexander et al., 1986). The members of multi-hospital system depend on each other to survive in the market. Thus, system membership is a tactic for horizontal integration which is used to reduce the dependence on other entities in the environment (Fareed & Mick, 2011). Hospitals within a multi-hospital system have more regional power and reduced competition in the area which have led to increased profits (Bai & Anderson, 2016; Melnick & Keeler, 2007; Capps & Dranove, 2004; Starkweather &

Carman, 1987). Melnick and Keeler (2007) suggested that members of multi-hospital system may demonstrate improved quality of services and may have greater bargaining power. This power exerted by the hospitals which are affiliated with a system, i.e. those hospitals that are members of a multi-hospital system, can help them to secure bigger pool of resources. Thus, acute care hospitals which are members of a multi-hospital system are more likely to implement PHM objectives of MU of EHRs. The amount of resources in these hospitals may also encourage them to have a higher level of MU of EHRs for PHM.

H2a: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are not members of multi-hospital system.

H2b: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to have higher level of MU of EHRs for PHM, as compared to those that are not members of multi-hospital system.

Organizations which are in resource-rich environments have access to a larger pool of resources. Such an environment can support the organization by enabling it to secure the necessary resources. For a hospital, an environment with paying patients is a resource-rich environment (Kazley & Ozcan, 2007) because it represents the economic conditions of the market (Zinn et al., 1997). Community wealth thus represents external resources in the environment. An environment with greater community wealth may be indicative of affluent area where the residents may afford private insurance and out-of-pocket healthcare costs (Kim & Thompson, 2012). Previous studies have used community wealth to operationalize munificence (Menachemi, Mazurenko, Kazley, Diana, & Ford, 2012; Menachemi et al., 2011; Kim & Thompson, 2012; Kazley & Ozcan, 2007; Hsieh, Clement, & Bazzoli, 2010; Fareed & Mick, 2011; Zinn et al., 1997; Trinh & Begun, 1999; Ginn & Young, 1992). Patients from such an environment can bring in revenue to the hospital through their cost sharing and insurance (Kim & Thompson, 2012; Ginn & Young, 1992). Further, EHR innovation may also attract patients who can afford to choose between hospitals; in order to attract these patients, hospitals may implement EHRs (Kazley & Ozcan, 2007; Fareed & Mick, 2011). An environment with lower community wealth may consist of a patient base which may be uninsured or not be able to afford cost-sharing, or be on Medicaid plans which has lower reimbursement rate as compared to private insurance. This reduces the revenue earned by the hospital which may make it difficult for the hospital to implement EHRs and use EHRs for PHM. This suggests that acute care hospitals operating in an area of greater community wealth have more resources which may encourage them to implement PHM objectives of MU of EHRs. It may also motivate these hospitals to use more modules of the EHRs and to use them EHRs extensively. Thus, the acute care hospitals in areas of greater community wealth may be more likely to have higher level of MU of EHRs for PHM.

H3a: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to implement the PHM

objectives of MU of EHRs, as compared to those located in the areas of lower community wealth.

H3b: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to have higher level of MU of EHRs for PHM, as compared to those located in the areas of lower community wealth.

Uncertainty. The amount of competition in the environment creates uncertainty for the organizations. Organizations have to compete with each other to secure resources from a limited pool. Organizations strategize to acquire more resources from the environment in a competitive market to stay viable. In this study, uncertainty is operationalized as the degree of market competition.

The degree of market competition affects the compliance of an organization with external constituencies (Banaszak-Holl et al., 1996). In a more competitive market, survival of the organization depends on how the resources are allocated across competitors (Banaszak-Holl et al., 1996). Organizations become more compliant with the external constituencies as the market competition increases. Previous studies have operationalized uncertainty as the degree of market competition (Banaszak-Holl et al., 1996; Balotsky, 2005; Alexander & Morrisey, 1989; Alexander, Morrisey, & Shortell, 1986; Zinn et al., 1999; Zinn et al., 1998; Ginn & Young, 1992; Fareed & Mick, 2011; Weech-Maldonado et al., 2009; Menachemi et al., 2011; Kim & Thompson, 2012; Kazley & Ozcan, 2007; Hsieh et al., 2010; Zinn et al., 1997). Hospitals in more competitive markets are more likely to adopt EHRs (Burke et al., 2002). If there are many hospitals in an area, the area becomes highly competitive in terms of attracting patients to their hospital. In a competitive market, hospitals may strategize to secure enough patients to maintain a competitive edge. In more competitive markets, the hospitals have a greater need to be proactive and to react (Balotsky, 2005; Bigelow & Mahon, 1989). Innovations such as EHRs may attract patients when they are given a choice of hospital with EHRs and those without (Kazley & Ozcan, 2007). EHRs could appeal to the patient population and thus help to bring more resources (i.e. patients) to the hospitals; whereas not implementing innovations such as EHRs could result in loss of their market share of the patients to more aggressive competitors (Zinn et al., 1999). Thus, greater market competition may encourage acute care hospitals to implement PHM objectives of MU of EHRs and to have a higher level of MU of EHRs for PHM.

H4a: All else being equal, acute care hospitals located in more competitive markets are more likely to implement the PHM objectives of MU of EHRs, as compared to those located in lesser competitive markets.

H4b: All else being equal, acute care hospitals located in more competitive markets are more likely to have higher level of MU of EHRs for PHM, as compared to those located in lesser competitive markets.

Interdependence. Organizations may create interdependent relationships with one another to gain more power in the market which could enable them to secure more resources from the environment. Organizations depend on other entities in interdependent relationships. The strategic behavior of focal organizations may alter according to these other entities and the focal organizations have to comply to maintain their interdependent relationships. Thus, interdependence can change organization's behavior in its pursuit to secure more resources from the environment. In this study, interdependence is operationalized as the ownership of the hospital, public payer mix of the hospital, stage of implementation of MU of EHRs, and the state regulatory environment applicable to the hospital.

Hospital ownership can influence the hospital's strategic behavior owing to their organizational missions. Previous studies have operationalized interdependence using ownership of the hospital (Kazley & Ozcan, 2007; Alexander et al., 1986; Proenca, Rosko, & Zinn, 2000; Kim & Thompson, 2012; Ginn & Young, 1992). For-profit hospitals operate to generate more profits for their investors (Clement & Grazier, 2000) while not-for-profit hospitals and government hospitals operate to serve the community (Kim & Thompson, 2012). For-profit hospitals place a strong emphasis on providing profitable services to generate return on investment for their investors (Greenlick, 1988). Hence, for-profit hospitals operate under greater efficiency to maximize their profits (Clement & Grazier, 2000; Harrison & Sexton, 2004). Not-for-profit hospitals are expected to serve the community in return of the tax advantages granted to them (Guggenheimer, 1988). Not-for-profit hospitals are not accountable to their investors and are not driven by profits (Proenca et al., 2000). Not-for-profit hospitals operate to provide more care to their communities which could be uncompensated and charitable (Kim & Thompson, 2012). For-profit hospitals have more aggressive pricing policies and better access to capital than not-for-profit hospitals (Pattison & Katz, 1983; Watt, Renn, Hahn, Derzon, & Schramm, 1986). Thus, for-profit hospitals are better positioned than not-for-profit hospitals to acquire resources from the environment. Previous studies have noted that for-profit hospitals are more likely to adopt EHRs (Zhang et al., 2013; Furukawa et al., 2008; Taylor et al., 2005; Amarasingham et al., 2008; Diana et al., 2015).

H5a: All else being equal, for-profit acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to not-for-profit acute care hospitals.

H5b: All else being equal, for-profit acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to not-for-profit acute care hospitals.

Government hospitals operate under political influence and are dependent on the political climate for the services they provide. Cutler, Feldman, and Horwitz (2005) noted that government hospitals are most likely to implement innovations such as Computerized Physician Order Entry (which is a module of EHRs) as compared to the other hospital ownership types. With the implementation of HITECH Act, the political influence on government acute care hospitals may be high; thus, encouraging them to implement PHM objectives of MU of EHRs and to achieve higher level of MU of EHRs for PHM.

H6a: All else being equal, government hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to the not-for-profit acute care hospitals.

H6b: All else being equal, government hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to the not-for-profit acute care hospitals.

Organizational resources may be affected by the regulatory changes in the environment (Banaszak-Holl et al., 1996; Zinn et al., 1998; Fareed & Mick, 2011; Weech-Maldonado et al., 2009). According to the HITECH Act, the CMS provides incentives to hospitals for demonstrating MU of EHRs (CMS, 2016, November 22). Hospitals can get payment adjustments for their Medicaid and Medicare patients if they fail to demonstrate MU (Medicare and Medicaid Programs Electronic Health Record Incentive Program-Stage 2, 2012). Hospitals that are dependent on public payers like CMS are more likely to respond to the financial incentives in the HITECH Act and modify their strategic behavior to take advantage of the incentives and avoid penalties. Hence, hospitals may comply and demonstrate MU of EHRs (Kazley & Ozcan, 2007; Fareed & Mick, 2011). Hospitals which have more number of Medicare and Medicaid patients (i.e. more public payer patients) have an opportunity to obtain more financial resources from CMS by implementing PHM objectives of MU of EHRs and by achieving a higher level of MU of EHRs for PHM. Previous studies have also used public payer mix to operationalize interdependence (Banaszak-Holl et al., 1996; Zinn et al., 1998; Kazley & Ozcan, 2007; Fareed & Mick, 2011; Weech-Maldonado et al., 2009).

H7a: All else being equal, acute care hospitals that have a higher public payer mix are more likely to implement the PHM objectives of MU of EHRs, as compared to those that have a lower public payer mix.

H7b: All else being equal, acute care hospitals that have a higher public payer mix are more likely to have higher level of MU of EHRs for PHM, as compared to those that have a lower public payer mix.

Under the ARRA Act of 2009, all eligible hospitals which demonstrate MU of EHRs could receive incentive payments from the CMS (CMS, 2016, November 22). Hospitals are dependent on the financial incentives they receive from the CMS. In order to receive the financial incentives, hospitals have to meet the requirements proposed by the HITECH Act. The HITECH Act proposed to achieve the MU of EHRs in three stages. As discussed in Chapter 2, the three PHM objectives are included as menu objectives in Stage 1 of MU of EHRs and the hospitals should meet at least one of the three PHM objectives (CMS, 2014 July). However, for the Stage 2 of MU of EHRs, the three PHM objectives are included as core objectives and hospitals should meet all three PHM objectives (CMS, 2014 July). Thus, to demonstrate MU of EHRs for Stage 2, the HITECH Act poses greater requirements on the hospitals.

H8a: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to implement PHM objectives of MU of EHRs, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

H8b: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to have a higher level of MU of EHRs for PHM, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

Laws and policies applicable for hospitals vary from state to state. Hospitals have to abide by the laws/policies to function in that state (Banaszak-Holl et al., 1996). This makes the hospitals dependent on their state regulatory environment. Previous studies have noted that regulations can force the hospitals to alter their output and are capable of changing their organizational structure (Coelen & Sullivan 1981; Worthington & Piro, 1982; Alexander & Fennell, 1986). Previously conducted studies have also used state laws to operationalize interdependence (Alexander & Morrisey, 1989; Weech-Maldonado et al., 2009). With the implementation of HITECH Act, states formed policies on reporting of PHM objectives of EHRs (HealthIT.gov, 2016, July 26). Some states have laws/policies around public health data reporting while some states do not (HealthIT.gov, 2016, July 26). This regulatory environment created by the states has a strong control over the hospitals and hence, hospitals are likely to comply with the laws/policies that are applicable to them.

H9a: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are in states with no laws/policies for public health data reporting.

H9b: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to have higher level of

MU of EHRs for PHM, as compared to those that are in states with no laws/policies for public health data reporting.

Summary of the Chapter

This chapter provided the definition of innovation and discussed the adoption of innovation in organizations. It also described the resource dependency theory and the development of the conceptual framework for this study. Based on the conceptual framework, research hypotheses for this study were discussed in detail.

The next chapter, chapter four, presents the research methodology for this study. It discusses the study design, study sample, data sources, measurement of the variables, and the analytical approach to test the research hypotheses proposed in this chapter.

CHAPTER FOUR: METHODOLOGY

This chapter describes the methodology of this study. The chapter starts with a description of the research design and its strengths and limitations. Further, the data sources, key measures, and variables used in this study are described, followed by a description of the statistical analytical plan. Finally, the ethical considerations, implications, and the limitations of the study are discussed in this chapter.

Research Design

The purpose of this study was to examine the factors associated with the implementation of PHM objectives of MU of EHRs in acute care hospitals in the U.S. and the factors associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S. The unit of analysis for this study was an individual acute care hospital in the U.S. This study used the multiple correlational research design. This was a retrospective cross-sectional study. The research design is illustrated in Figure 2.

Figure 2: Multiple Correlational Research Design

$$r_{x1\ x2...xn*O}$$

Where

r = Correlation coefficient

x = Cause

O = Effect

In the context of this study, the cause “x” represents the organizational and environmental factors and the effect “O” represents the MU of EHRs for PHM. Since it is possible that multiple factors are associated with the MU of EHRs for PHM, this study used the multiple correlational research design. Although this research design has its advantages and disadvantages, it fits appropriately for the nature of this study and the data available.

Study validity helps to draw confident conclusions about the truth or falsity of study hypothesis from the results of the study (Cherulnik, 2001, pp.11-12). A research design should have good construct, internal, and external validity. For this study, the threats to construct validity are minimal. There is no contact between the researcher and the study participant, so there is no threat of reactive arrangements. Additionally, this study uses administrative data, so there is no pretest sensitization or linguistic or cultural bias. In this study, there is a possibility that an extraneous event may be responsible for the relationship between organizational and environmental factors and the MU of EHRs for PHM. This threat is reduced by identifying organizational and environmental factors associated with the MU of EHRs for PHM through the literature review and the use of a theoretical framework. However, the possibility of an extraneous event remains. Temporal effects are not a threat in this study because this is a cross-sectional study. Group composition effects are not a threat to internal validity in this study because this study does not use two or more groups. This study has one homogenous sample and does not compare between groups within the sample. Since, this study is a cross-sectional study, there is no risk of selective sample attrition. Furthermore, this study considers the full range of the data and hence there is no threat due to statistical regression effects.

In this study, there are no threats from non-representative sampling because this study uses all non-federal, non-critical access, acute care hospitals from the American Hospital Association (AHA) Annual Survey database which is an administrative database representative of the national sample. This eliminates selective sampling. Finally, there is no threat due to non-representative research context because the study is based on real behaviors of organizations in their natural settings. The validity of this study is summarized according to the validity scorecard proposed by Cherulnik (2001) in Table 1.

Table 1: Validity Scorecard

Construct Validity	
Reactive arrangements	+ No contact between researcher and participants
Pretest sensitization	+ Uses survey data, so no pretest sensitization
Linguistic/cultural bias	+ Uses survey data, so no linguistic or cultural bias
Internal Validity	
Extraneous events	- A possible third variable cause is a matter of concern
Temporal effects	+ Cross-sectional data, so no risk of temporal effects
Group composition effects	+ One group
Temporal X group composition effects	+ One group and no temporal effects
Selective sample attrition	+ No attrition because it is a cross-sectional data
Statistical regression effects	+ Entire range of data is considered
External Validity	
Non-representative sampling	+ Research is based on administrative data from large, representative sample such as AHA annual survey database
Non-representative research context	+ Research is based on real behaviors in natural settings

Data Sources

This section describes the data sources that are used to obtain the variables necessary for this study. This study used the American Hospital Association (AHA) Annual Survey Database 2013 (American Hospital Association, 2014), Centers for Medicare and Medicaid Services (CMS) Stage 1 and Stage 2 MU Data Files 2015 (CMS, 2016, October 27), the Area Health Resource Files (AHRF) 2015-2016 (Bureau of Health Workforce, 2016), and the state health information technology (HIT) policy levers compendium 2011-2013 (HealthIT.gov, 2016, July 26) as the data sources. These datasets are described below:

1. AHA Annual Survey Database 2013:

The American Hospital Association (AHA) conducts the AHA annual survey which is a voluntary survey sent to all hospitals identified by the AHA as open and operating (American Hospital Association, 2014). This survey is sent to both the AHA hospital members and non-AHA hospital members. The AHA annual survey database contains primarily the responses from the AHA annual survey which are supplemented with the data obtained from the AHA registration database, the U.S. Census Bureau, and other accrediting organizations. Although this survey is voluntary, the response rate is about 80% and the non-respondent values are imputed using an estimation process. AHA annual survey database, thus contains the complete universe of hospitals, which is about 6,300, in the U.S. and U.S. territories. AHA has been used extensively for health services research and market analysis (Alexander et al., 1986; Alexander & Fennel, 1986; Alexander & Morrisey, 1989; Bazzoli et al., 2003; Diana et al., 2014; Kazley & Ozcan, 2007; Kim & Thompson, 2012; Menachemi et al., 2011; Trinh & Begun, 1999; Zinn et al., 1997). This dataset can also be linked to other datasets using the Medicare Provider Number and the National Provider Identification Number.

For this study, organizational factors such as size, ownership, public payer mix, and membership of multi-hospital system were obtained from the AHA annual survey database. The control variable, i.e. teaching status of the hospital was obtained from the AHA annual survey database. The number of beds in the hospital, used to calculate the Herfindahl-Hirschman Index (HHI), was also obtained from this data. In this study, the independent and control variables were lagged by one year to address temporal precedence of cause and effect. Since the dependent variables were measured from the year 2014, the AHA annual survey database for 2013 was used in this study.

2. <u>CMS Stage 1 and Stage 2 Meaningful Use Data Files:</u>

All hospitals that implement the MU of EHRs submit their attestation of implementation of MU of EHRs to the CMS to receive payment adjustments. Based on the stage of implementation of MU that the hospitals file their attestation for, CMS maintains Stage 1 and Stage 2 MU data files (CMS, 2016, October 27). These data files contain information on attestation of all the eligible hospitals. Stage 1 file contains attestation information on hospitals which fulfill the Stage 1 criteria of MU and Stage 2 file contains attestation information on hospitals which fulfill the Stage 2 criteria of MU. These datasets are updated every quarter. These files have information on each EHR objective and the implementation status among eligible hospitals who have submitted their attestation to CMS. These datasets were linked to the AHA dataset using the Medicare Provider Number.

For this study, the organizational factor of stage of implementation of MU was obtained from this dataset. The dependent measures i.e. the implementation of PHM objectives of MU of EHRs were also obtained from the CMS Stage 1 and Stage 2 MU data files. For this study, the data for stage of implementation of MU and dependent variables were obtained for the year 2014 from the data file which was updated in the third quarter of the year 2015 and downloaded during the fourth quarter of the year 2015.

3. AHRF Data 2015-2016:

The AHRF database is maintained by the U.S. Department of Health and Human Services, Health Resources and Services Administration (Bureau of Health Workforce, 2016). The AHRF database provides information on health resources (such as healthcare facilities, health professions, health status), socioeconomic determinants (such as per capita income), and environmental characteristics (such as rurality) which affect the healthcare demand. The AHRF database contains information from about 50 sources including American Medical Association, Bureau of Labor Statistics, Centers for Disease Control and Prevention National Center for Health Statistics, etc. (Bureau of Health Workforce, 2016). The AHRF data contains geographical codes and descriptors which enable the linking of AHRF data with other datasets. In this study, the AHRF data was linked with the above mentioned two datasets using the FIPS county code. For this study, the environmental factor - per capita personal income and control variable - rurality of the market area was obtained using the AHRF dataset. The total number of beds in the county, used to compute the Herfindahl-Hirschman Index (HHI), was also obtained from the AHRF data. This study used the 2015-2016 AHRF dataset which contains data for the year 2013.

4. <u>State HIT Policy Levers Compendium 2011-2013:</u>

The state health information technology (HIT) policy levers compendium was developed by the Office of National Coordinator for HIT (ONC) with the support of states (HealthIT.gov, 2016, July 26). This compendium is a directory of all HIT policies for all states. It describes each policy lever and its uses to improve HIT and interoperability. State examples are provided where applicable. This study identified the policies related to the use of HIT for PHM from this compendium. Public health surveillance was the only one policy lever which accurately fit the study objectives. This policy was described as "local, state, and federal public health agencies rely on immunization, syndromic surveillance, and reportable lab results data to carry out their surveillance activities under state and federal laws. States can require that public health surveillance data submissions be sent via a designated HIE, or a certified/registered/deemed HIE. States or public health entities can require that public health surveillance data submissions be sent electronically to improve interoperability. Local and state agencies have the flexibility to set parameters around how providers, hospitals, and other entities transport this data" (HealthIT.gov, 2016, July 26).

This data file helps to identify the states which have policies categorized as the "public health surveillance" policy lever (See Appendix for detailed state policies under the public health surveillance policy lever). For this study, the environmental factor of state laws/policies was obtained from this dataset. The data on state laws/policies obtained are from years 2011-2013.

Study Universe, Population, and Sample

This study examined the implementation of PHM objectives of MU of EHRs and the level of MU of EHRs for PHM in acute care hospitals in the U.S. Hence, the unit of analysis in this study was an individual acute care hospital in the U.S. The universe for this study was all open and operating, non-federal, non-critical access, acute care hospitals in the 50 U.S. states and the District of Columbia. This universe did not include federal hospitals because the operations of federal hospitals differs from that of non-federal hospitals in terms of policies, financing, and patient population. Critical access hospitals were excluded from this universe because they are certified under different conditions as compared to the acute care hospitals (Scalise, 2004). This universe did not include any hospitals with specialized functions, for example, psychiatric or children's hospitals. This universe also did not include hospitals operating in U.S. territories of American Samoa, Federal States of Micronesia, Guam, Marshall Islands, Northern Mariana Islands, Palau, Puerto Rico, and Virgin Islands.

The study population is non-federal, non-critical access, acute care hospitals within the 50 U.S. states and the District of Columbia who have responded to the AHA annual survey database. The AHA annual survey database is a nationally representative dataset containing data on all non-federal hospitals in the U.S. (American Hospital Association, 2014). The study population was merged with the AHRF dataset and CMS Stage 1 and Stage 2 MU data files. Since the dependent variables are obtained from CMS Stage 1 and Stage 2 MU data files, hospitals which were in the study population but not the CMS Stage 1 and Stage 2 MU data files were excluded from the study sample. The final empirical study sample was obtained by merging these three datasets and excluding invalid and missing observations. This study examined whether this study sample was representative of the study population by conducting one-sample t-test on the continuous independent variables and one sample test of proportions on the categorical independent variables.

Measurement

This section defines the market area for the individual acute care hospital in the U.S. followed by the description and measurement of the independent, dependent variables, and control variables described in the conceptual model.

Market Area

This study used the resource dependency theory (RDT) which suggests that each hospital is dependent on its environment for resources. In order to examine the resources in the environment, it is necessary to define the boundaries for this environment. This environment is known as the hospital market area. Market area can be defined from an individual hospital perspective or from overall market perspective. Since the unit of analysis for this study is the individual acute care hospital, the market area is defined from the individual hospital perspective.

There are three empirical approaches to define the market area from an individual hospital perspective: 1). Geopolitical boundaries where the market area is the county where the hospital is located, 2). Distances among hospitals where the market area is the 15-mile radius around the hospital, and 3). Patient origin where the market area is defined by the proportion of patients in the community utilizing the hospital in that community

(Garnick, Luft, Robinson, & Tetreault, 1987). This study used the geopolitical boundaries to define the market area because of the availability of data and comparability between counties. Thus, for this study, the market area for individual acute care hospital in the U.S. was defined as the county where the hospital is located.

Dependent Variables

There were three objectives identified as PHM objectives from the MU objectives of EHRs: 1) submission of electronic data to immunization registries, 2) submission of electronic data on reportable laboratory results to public health agencies, and 3) submission of electronic syndromic surveillance data to public health agencies. The dependent variables used in this study are based on these three objectives.

- Use of EHRs to submit electronic data to immunization registries (IMMUNIZATION):

Use of EHRs to submit electronic data to immunization registries was defined as whether the hospital has met the MU objective of submission of electronic data to immunization registries. Hospitals can claim exclusion to this objective if: 1. hospital does not administer any of the immunizations to any of the populations for which data is collected by their jurisdiction's immunization registry or immunization information system during the EHR reporting period, 2. hospital operates in a jurisdiction for which no immunization registry or immunization information system is capable of accepting the specific standards required for certified EHR technology at the start of their EHR reporting period, 3. hospital operates in a jurisdiction where no immunization registry or immunization information system provides information timely on capability to receive immunization data, or 4. hospital operates in a jurisdiction for which no immunization registry or immunization information system that is capable of accepting the specific standards required by certified EHR technology at the start of their EHR reporting period can enroll additional eligible hospitals (CMS, 2016, October 27).

IMMUNIZATION is a categorical variable which was obtained from the CMS Stage 1 and Stage 2 MU data files. This variable was coded as 1 if the hospital met this objective and as 0 if the hospital did not meet this objective in 2014. If the hospital claimed exclusion for this objective in 2014, it was also coded as 0 since the hospital did not use EHRs to submit electronic data to immunization registries in practice.

- Use of EHRs to submit electronic data on reportable laboratory results to public health agencies (LABORATORY):

Use of EHRs to submit electronic data on reportable laboratory results to public health agencies was defined as whether the hospital has met the MU objective of submission of electronic data on reportable laboratory results to public health agencies. Hospitals can claim exclusions to this objective if: 1. hospital operates in a jurisdiction for which no public health agency is capable of receiving electronic reportable laboratory results in the specific standards required for certified EHR technology at the start of their EHR reporting period, 2. hospital operates in a jurisdiction for which no public health agency provides information timely on capability to receive electronic reportable laboratory results, or 3. hospital operates in a jurisdiction for which no public health agency that is capable of accepting the specific standards required by certified EHR technology at the start of their EHR reporting period can enroll additional eligible hospitals (CMS, 2016, October 27).

LABORATORY is a categorical variable which was obtained from the CMS Stage 1 and Stage 2 MU data files. This variable was coded as 1 if the hospital met this objective and as 0 if the hospital did not meet this objective in 2014. If the hospital claimed exclusion for this objective in 2014, it was also coded as 0 since the hospital did not use EHRs to submit electronic data on reportable laboratory results to public health agencies in practice.

- Use of EHRs to submit electronic syndromic surveillance data to public health agencies (SURVEILLANCE):

Use of EHRs to submit electronic syndromic surveillance data to public health agencies was defined as whether the hospital has met the MU objective of submission of electronic syndromic surveillance data to public health agencies. Hospitals can claim exclusion to this objective if: 1. hospital does not have an emergency or urgent care department, 2. hospital operates in a jurisdiction for which no public health agency is capable of receiving electronic syndromic surveillance data in the specific standards required by certified EHR technology at the start of their EHR reporting period, 3. hospital operates in a jurisdiction where no public health agency provides information timely on capability to receive syndromic surveillance data, or 4. hospital operates in a jurisdiction for which no public health agency that is capable of accepting the specific standards required by certified EHR technology at the start of their EHR reporting period can enroll additional eligible hospitals (CMS, 2016, October 27).

SURVEILLANCE is a categorical variable which was obtained from the CMS Stage 1 and Stage 2 MU data files. This variable was coded as 1 if the hospital met this objective and as 0 if the hospital did not meet this objective in 2014. If the hospital claimed exclusion for this objective in 2014, it was also coded as 0 since the hospital did not use EHRs to submit electronic surveillance data to public health agencies in practice.

- Level of MU of EHRs for PHM (LEVEL):

The level of MU of EHRs for PHM was a composite measure that was created using the data on the aforementioned three PHM objectives. The level of MU of EHRs for PHM was defined by the number of PHM objectives implemented by the hospital. If the hospitals claimed exclusion for an objective, it was considered that the hospital did not implement that objective. If the hospitals implemented any one of the three aforementioned objectives, the level of MU of EHRs for PHM was coded as 1 or minimum level of MU of EHRs for PHM. If the hospitals implemented any two of the three aforementioned objectives, the level of MU of EHRs for PHM was coded as 2 or moderate level of MU of EHRs for PHM. If the hospitals implemented all three of the aforementioned objectives, the level of MU of EHRs for PHM was coded as 3 or comprehensive level of MU of EHRs for PHM. If the hospitals did not implement any of the three aforementioned objectives, the level of MU of EHRs for PHM was coded as 0 or no MU of EHRs for PHM. The data used to code this variable was obtained from the CMS Stage 1 and Stage 2 MU data files.

Independent Variables

The independent variables in this study are the organizational and environmental factors that are associated with the implementation of MU of EHRs for PHM and the level of MU of EHRs for PHM by acute care hospitals in the U.S. These factors were identified in Chapter 3 using resource dependency theory. In order to ensure that the cause precedes the effect, all of the independent variables except one were lagged by one year (i.e. measured in 2013). The stage of implementation of MU is the only variable that was not lagged (i.e. it was measured in 2014). Although stage of implementation of MU was not lagged, the cause i.e. stage of implementation of MU precedes the effect i.e. the implementation of PHM objectives of MU of EHRs. According to the EHRs incentives program, CMS established a timeline for the hospitals where hospitals had to progress to Stage 2 of MU implementation after demonstrating 2 years of Stage 1 of MU implementation (exception of 3 years for those hospitals which began demonstration of Stage 1 of MU implementation in 2011; CMS, August 2012). This implies that the hospitals progress to Stage 2 of implementation of MU and hence must meet all the objectives of Stage 2. Thus, the cause precedes the effect. This strengthened the research design in terms that the organizational and environmental factors which are the putative causes precede the implementation of PHM objectives of EHRs and the level of MU of EHRs for PHM which are the key outcome variables.

Organizational Factors

- Size of the hospital (BEDS):

The munificence construct was operationalized as the size of the hospital. The size of the hospital is a measure of abundancy of resources available, where the larger hospital has more resources than the smaller hospital. The size of the hospital was measured by the total number of hospital unit beds which are set up and staffed (Banaszak-Holl et al., 1996; Zinn et al., 1999; Zinn et al., 1998; Kim & Thompson, 2012; Kazley & Ozcan, 2007; Alexander & Morrisey, 1989). The total number of hospital unit beds which are set up and staffed is a continuous variable which was obtained from the AHA 2013 data.

- Public-payer mix for the hospital (PAYER):

The interdependence construct was operationalized as the public-payer mix of the hospital. The public-payer mix is a measure of interdependence of the hospital on the public payers such as Medicare and Medicaid. The higher proportion of public payer mix represents higher interdependence on the public payers such as Medicare and Medicaid. The public-payer mix was measured as the proportion of services provided for Medicare and Medicaid patients (Banaszak-Holl et al., 1996; Zinn et al., 1998; Kazley & Ozcan, 2007; Fareed & Mick, 2011; Weech-Maldonado et al., 2009). The proportion of services provided for Medicare and Medicaid patients was calculated as follows:

$$Proportion\ of\ services\ provided\ for\ Medicare\ and\ Medicaid\ patients$$
$$= \frac{\begin{array}{c}Number\ of\ hospital\ inpatient\ Medicare\ days\\ +Number\ of\ hospital\ inpatient\ Medicaid\ days\end{array}}{Total\ number\ of\ hospital\ inpatient\ days}$$

The number of hospital inpatient Medicare days, number of hospital inpatient Medicaid days, and the total number of hospital inpatient days are continuous variables which were obtained from the AHA 2013 data.

- System membership (SYSTEM):

The munificence construct was operationalized as the membership of multi-hospital system. System membership provides access to bigger pool of resources within the multi-hospital system and also increases the bargaining power of the hospital in the environment (Alexander et al., 1986; Fareed & Mick, 2011; Bai & Anderson, 2016; Melnick & Keeler, 2007; Capps & Dranove, 2004; Starkweather & Carman, 1987). The system membership status of the hospital is a categorical variable which was obtained from the AHA 2013 data. The AHA data identifies those hospitals which are system members based on the information collected during the survey (American Hospital Association, 2014). In the AHA data, system membership is left blank if sufficient information does not exist to classify them as system members (American Hospital Association, 2014). In such cases, the hospitals were considered as non-system members. System membership status was coded as 1 if the hospital is a system member and as 0 if the hospital was not a system member.

- Ownership of the hospital (FORPROFIT, PUBLIC):

The interdependence construct was operationalized as the ownership of the hospital (Kazley & Ozcan, 2007; Alexander et al., 1986; Proenca et al., 2000; Kim & Thompson, 2012; Ginn & Young, 1992). Ownership is defined as the type of authority that is responsible for establishing policy and controlling the overall operating of the hospital. This is a categorical variable which was obtained from AHA 2013 data. For the ownership of hospital, two dummy variables were created. FORPROFIT was categorized as 1 if the hospitals were investor-owned for-profit hospitals and as 0 if otherwise. PUBLIC was categorized as 1 if the hospitals were non-federal government hospitals and as 0 if otherwise.

- Stage of implementation of MU of EHRs (STAGEDUMMY):

The interdependence construct was operationalized as the stage of implementation of MU of EHRs. Stage of implementation of MU of EHRs is defined as the stage of implementation of MU of EHRs for which the hospital submitted attestation to the CMS. This data was obtained from the 2014 CMS Stage 1 and Stage 2 MU data files. This is a dummy variable where STAGEDUMMY was coded as 1 if the hospital provided attestation for demonstration Stage 2 of implementation of MU of EHRs and was coded as 0 if otherwise.

Environmental Factors

- Per capita personal income of the county (INCOME):

The munificence construct was operationalized as the community wealth. Community wealth was measured as the per capita personal income of the county (Menachemi et al., 2012; Menachemi et al., 2011; Kim & Thompson, 2012; Kazley & Ozcan, 2007; Hsieh et al., 2010; Fareed & Mick, 2011; Zinn et al., 1997; Trinh & Begun, 1999; Ginn & Young, 1992). The per capita personal income of the market area in which the hospital is located represents abundancy of resources in the environment. Higher per capita personal income of the market area (which is county in this study) represents more resources as compared to the market areas with lower per capita personal income. The per capita personal income of the county is a continuous variable which was obtained from the AHRF 2013 data.

- Competition in the market (HHI):

The uncertainty construct was operationalized as the market competition. Greater market competition represents greater uncertainty of resources as compared to lower market competition. Market competition is measured by the Herfindahl-Hirschman Index (HHI) (Banaszak-Holl et al., 1996; Balotsky, 2005; Alexander & Morrisey, 1989; Alexander et al., 1986; Zinn et al., 1999; Zinn et al., 1998; Ginn & Young, 1992; Fareed & Mick, 2011; Weech-Maldonado et al., 2009; Menachemi et al., 2011; Kim & Thompson, 2012; Kazley & Ozcan, 2007; Hsieh et al., 2010; Zinn et al., 1997). HHI is a standard measure of market competition which is used in economic analyses and is calculated as the sum of squared market shares (Department of Justice and Federal Trade Commission, 1993). Previous studies have used the number of beds staffed and set up to calculate the market share of the hospital (Banaszak-Holl et al., 1996; Zinn et al., 1997).

$$Market\ share\ of\ a\ hospital = \frac{Number\ of\ beds\ staffed\ and\ set\ up\ in\ the\ hospital}{Total\ number\ of\ beds\ staffed\ and\ set\ up\ in\ the\ county}$$

$$Herfindahl - Hirschman\ Index\ (HHI) = Sum\ of\ squared\ market\ shares\ of\ hospitals\ in\ the\ county$$

The number of beds staffed and set up in a hospital is a continuous variable which was obtained from the AHA 2013 data. The total number of beds staffed and set up in the county is a continuous variable which was obtained from the AHRF 2013 data.

- State laws/policies (LAW):

Previous studies have operationalized interdependence using the state laws applicable to the organizations (Coelen & Sullivan 1981; Worthington & Piro, 1982; Alexander & Fennell, 1986). The ONC in coordination with states created the State HIT policy levers compendium (HealthIT.gov, 2016, July 26). Public health surveillance was the only policy lever in this compendium that focused on the PHM objectives of submission of immunization data, reportable laboratory results, and syndromic surveillance data. This policy lever was described as “local, state, and federal public health agencies rely on immunization, syndromic surveillance, and reportable lab results data to carry out their surveillance activities under state and federal laws. States can require that public health surveillance data submissions be sent via a designated HIE, or a certified/registered/deemed HIE. States or public health entities can require that public health surveillance data submissions be sent electronically to improve interoperability. Local and state agencies have the flexibility to set parameters around how providers, hospitals, and other entities transport this data" (HealthIT.gov, 2016, July 26). According to the state HIT policy levers compendium, Alaska, California, Colorado, Illinois, Iowa, Kentucky, Maryland, Michigan, Nebraska, New Hampshire, New Jersey, Oregon, Pennsylvania, Texas, and West Virginia had set up policies/laws with respect to the public health surveillance policy lever before 2014.

The policies under this public health surveillance policy lever varied from state to state; however, the scope of these policies are limited to the definition of the public health surveillance policy lever (See Appendix for detailed description of the state policies under public health surveillance policy lever). Due to the smaller sample size, it was not possible to capture the differences in each policy. Nonetheless, a documented public health reporting policy may encourage the hospitals to use EHRs for PHM. State laws/policies was categorized as follows: the states which had documented public health surveillance policy were coded as 1, while the states which had no documented public health surveillance policy were coded as 0. Since Alaska, California, Colorado, Illinois, Iowa, Kentucky, Maryland, Michigan, Nebraska, New Hampshire, New Jersey, Oregon, Pennsylvania, Texas, and West Virginia had policies/laws with respect to the public health surveillance policy lever, the hospitals in these states were coded as 1 for LAW; and the hospitals in the rest of the states were coded as 0 for LAW.

Control variables

This study controlled for teaching status of the hospital and the geographic location of the hospital.

- Teaching status (TEACH):

Teaching status of the hospital was defined by whether the hospital is a member of Council of Teaching Hospital of the Association of American Medical Colleges (COTH) (American Hospital Association, 2014). This is a categorical variable which was obtained from the AHA 2013 data. It was categorized as 1 if the hospital is a member of COTH and as 0 if the hospital is not a member of COTH.

- Geographic location (RURALITY):

Geographic location was defined by the urban or rural geographic location of the market area of the hospital. The 2013 Rural Urban Continuum codes as proposed by the U.S. Department of Agriculture Economic Research Services categorizes each county into metropolitan and non-metropolitan counties. The metropolitan counties are further categorized based on their population size (coded as 01 if urban population of 1 million or more; 02 if urban population of 250,000 – 1,000,000; 03 if urban population of fewer than 250,000). The non-metropolitan counties are further categorized based on their degree of urban population and their distance from metro area (coded as 04 if urban population of 20,000 or more and adjacent to metro area; 05 if urban population of 20,000 or more and not adjacent to metro area; 06 if urban population of 2,500-19,999 and adjacent to metro area; 07 if urban population of 2,500-19,999 and not adjacent to metro area; 08 if completely rural or less than 2,500 urban population and adjacent to metro area; 09 if completely rural or less than 2,500 urban population and not adjacent to metro area). For this study, RURALITY was categorized into 2 groups: coded as 1 for metropolitan counties (coded 01 to 03 above) and coded as 0 for non-metropolitan counties (coded 04 to 09 above). The Rural-Urban continuum codes for the county were obtained from the AHRF 2013 data.

The Table 2 summarizes the measures and variables described above along with their operational definitions, type, and data source.

Table 2: Summary of Dependent, Independent, and Control Variables

Measure	Variable	Operational Definition	Variable Type	Year of Measurement	Data Source
Dependent Variables					
Use of EHRs to submit electronic data to immunization registries	Submission of electronic data to immunization registries (IMMUNIZATION)	Whether or not the hospital has met the MU objective of submission of electronic data to immunization registries in 2014	Categorical variable 1 = Yes 0 = No	2014	CMS Stage 1 and Stage 2 meaningful use data files 2015
Use of EHRs to submit electronic data on reportable laboratory results to public health agencies	Submission of electronic data on reportable laboratory results to public health agencies (LABORATORY)	Whether or not the hospital has met the MU objective of submission of electronic data on reportable laboratory results to public health agencies in 2014	Categorical variable 1 = Yes 0 = No	2014	CMS Stage 1 and Stage 2 meaningful use data files 2015
Use of EHRs to submit electronic syndromic surveillance data to public health agencies	Submission of electronic syndromic surveillance data to public health agencies (SURVEILLANCE)	Whether or not the hospital has met the MU objective of submission of electronic syndromic surveillance data to public health agencies in 2014	Categorical variable 1 = Yes 0 = No	2014	CMS Stage 1 and Stage 2 meaningful use data files 2015
Level of MU of EHRs for PHM	Level of MU of EHRs for PHM (LEVEL)	Number of PHM objectives implemented by the hospital in 2014	Categorical variable 3 = Comprehensive level of MU for PHM 2 = Moderate level of MU for PHM	2014	CMS Stage 1 and Stage 2 meaningful use data files 2015

Measure	Variable	Operational Definition	Variable Type	Year of Measurement	Data Source
			1 = Minimum level of MU for PHM 0 = No MU for PHM		
Munificence					
Size of the hospital	Number of hospital beds (BEDS)	Total number of hospital unit beds staffed and set up in 2013	Continuous variable	2013	AHA Annual Survey Data 2013
Member of multi-hospital system	System membership (SYSTEM)	Whether the hospital is a member of a system of hospitals in 2013	Categorical variable 1 = Yes 0 = No	2013	AHA Annual Survey Data 2013
Community wealth	Per capita personal income in the county (INCOME)	Per capita personal income in the county in 2013	Continuous variable	2013	AHRF Data 2015-2016
Uncertainty					
Market competition	Herfindahl-Hirschman Index (HHI)	Herfindahl-Hirschman Index = sum of squared market shares of a hospital in a market area. Market share is calculated as follows: Number of staffed and set up beds in the hospital/Total number of staffed and set up beds in the county	Continuous variable	2013	AHRF Data 2015-2016 and AHA Annual Survey Data 2013

Measure	Variable	Operational Definition	Variable Type	Year of Measurement	Data Source
Interdependence					
Ownership of the hospital	For-profit ownership of the hospital (FORPROFIT)	Type of authority responsible for establishing policy concerning overall operation of the hospital	Categorical variable 1 = Investor owned, for-profit 0 = Otherwise	2013	AHA Annual Survey Data 2013
Ownership of the hospital	Government ownership of the hospital (PUBLIC)	Type of authority responsible for establishing policy concerning overall operation of the hospital	Categorical variable 1 = Non-federal government 0 = Otherwise	2013	AHA Annual Survey Data 2013
Public payer mix	Proportion of services provided for Medicare and Medicaid patients (PAYER)	This value is calculated as: (number of hospital inpatient Medicare days + number of hospital inpatient Medicaid days) /total number of hospital inpatient days	Continuous variable	2013	AHA Annual Survey Data 2013
Stage of implementation of MU	Stage of implementation of MU of EHRs (STAGEDUMMY)	Stage of implementation of MU of EHRs for which the hospital submitted attestation to the CMS	Categorical variable 1 = Stage 2 of MU 0 = Otherwise	2014	CMS Stage 1 and Stage 2 meaningful use data files 2015
State laws/policies	State laws (LAW)	Whether a state law/policy for public health data reporting is documented in the state where the hospital is located	Categorical variable 1 = State policy documented	2011-2013	State HIT Policy Levers Compendium

Measure	Variable	Operational Definition	Variable Type	Year of Measurement	Data Source
			0 = No state policy documented		
Control Variables					
Teaching status	Teaching status of the hospital (TEACH)	Whether the hospital is a member of COTH	Categorical variable 1 = Yes 0 = No	2013	AHA Annual Survey Data 2013
Geographic location	Rural-urban geographic location of the hospital (RURALITY)	Rurality of the hospital based on its geographic location and Rural-Urban Commuting codes	Categorical variable 1 = Metropolitan 0 = Non-metropolitan	2013	AHRF Data 2015-2016

Statistical Analysis Plan

This study used SAS 9.4 (SAS Institute Inc., Cary, North Carolina) for data manipulation and STATA 14.0 for statistical analysis (StataCorp LP., College Station, TX). The statistical significance for this study was assessed at a two-sided p-value of < 0.05. A p-value of < 0.10 was considered to be marginally significant.

Univariate Analyses

Descriptive statistics were calculated for each dependent, independent, and control variable. The mean, median, minimum, maximum, and standard deviation were calculated for each continuous variable. Frequency and percentage were calculated for each categorical variable. The descriptive statistics were used to identify outliers, missing data, and skewness in the distribution of data. Data were log transformed in case of skewed data. One sample t-test and one sample test of proportions were used to compare the study sample with the study population. Pearson's correlation test was used to check for multi-collinearity between the variables.

Multivariate Analyses

The first aim of this study was to examine the organizational and environmental factors that are associated with the implementation of any of the PHM objectives of MU of EHRs in acute care hospitals in the U.S. This aim can be further sub-divided as three study objectives: 1. To examine the organizational and environmental factors that are associated with the submission of electronic data to immunization registries, 2. To examine the organizational and environmental factors that are associated with the submission of electronic data on reportable laboratory results to public health agencies, and 3. To examine the organizational and environmental factors that are associated with the submission of electronic syndromic surveillance data to public health agencies. These three objectives were measured by the three dependent variables – submission of electronic data to immunization registries, submission of electronic data on reportable laboratory results to public health agencies, and submission of electronic syndromic surveillance data to public health agencies. Each of these three variables was a binary categorical variable. Hence, logistic regressions were appropriate. Further, the unit of analysis i.e. the individual hospital is nested within states. As discussed earlier, states have policies which can influence the submission of electronic data for PHM. Ordinary logistic regression assumes independence of observations but when the hospitals are nested within clusters, there may be correlation among observations within a cluster (Hedeker, 2003). To account for the hierarchical nature of the data, three separate mixed effects logistic regression models were used to address the first aim of this study.

The second aim of this study was to examine the organizational and environmental factors that are associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S. The level of MU of EHRs for PHM was defined as the number of PHM objectives implemented using EHRs by the hospital. If no PHM objectives were implemented, it was defined as no MU of EHRs for PHM; if any one PHM objective was implemented, it was defined as minimum level of MU of EHRs for PHM; if any two of the PHM objectives were implemented, it was defined as moderate level of MU of EHRs for PHM; if all three PHM objectives were implemented, it was defined as comprehensive level of MU of EHRs for PHM. Thus, it would be possible to define the level of MU of EHRs for PHM as a count variable. However, the range of this variable was from 0 to 3. The count data is censored. Hence, a Poisson regression was not considered appropriate. This variable was categorized based on any PHM objective that was implemented by the hospitals. It is not certain that only one specific objective was implemented by all the hospitals that are in the minimum level of MU or only two specific objectives were implemented by all the hospitals that are in the moderate level of MU. This suggests there is no ordering to the data. Hence, this variable was considered as a nominal variable. The level of MU of EHRs for PHM was treated as a polychotomous variable with four categories. Hence, multinomial logistic regression was considered appropriate. As discussed earlier, the hospitals are nested within states which may cause correlations among observations within a cluster. Hence, a mixed effects multinomial logistic regression was used to address the second aim of this study.

Mixed Effects Logistic Regression. When the dependent variable has only two response categories, logistic regression is used for analysis. For a binary dependent variable Y predicted by the explanatory variable X, the ordinary logistic model can be represented as (Quené & Van den Bergh, 2008):

$$Y_i = \beta_0 + \beta_1 X_i + (e_i)$$

The only random term in this equation is e_i which represents the part of Y which is not captured by the regression equation. The explanatory variable X is a fixed effect which means that β_0 and β_1 are assumed to be fixed throughout the study population. The *i* observations are assumed to be sampled independently from the study population. However, the hospitals are grouped by the states in which they are located. This indicates that the observations on the hospital level are correlated and they depend on the higher-level unit, i.e. state, in this study. The basic equation described above can be modified to accommodate the random effect of the state u. The mixed effects logistic regression can be expressed as follows (Quené & Van den Bergh, 2008):

$$Y_{ij} = \gamma_0 + \gamma_1 X + (u_{0j} + e_{ij})$$

Where i = level 1 units, i.e. nested observations

j = level 2 units, i.e. clusters

u_{0j} = deviation of the jth state average from the overall intercept γ_{00}

This captures the correlation between the observations within states.

Mixed Effects Multinomial Logistic Regression. The multinomial logistic regression pairs each category with a baseline category (Agresti, 2002). The mixed effects multinomial logistic regression model is an extension of the multinomial logistic regression (Hedeker, 2003). Mixed effects model allows for inclusion of both random and fixed effects. Assuming i = 1, 2, … N level 2 units and j = 1, 2, …, n_i level 1 units nested within each level 2 unit, mixed effects multinomial logistic regression can be represented as (Hedeker, 2003):

$$log\frac{p_{ijc}}{p_{ij1}} = u'_{ij}\gamma_c + z'_{ij}v_{ic}$$

Where i = level 2 units, i.e. clusters

j = level 1 units, i.e. nested observations

c = response categories coded as 1, 2, … C

γ_c = regression effects

v_{ic} = random effects

In this study, the hospital observations were level 1 units which are nested under the 50 U.S. states and the District of Columbia. The 50 U.S. states and the District of Columbia were the level 2 units.

Empirical model. The empirical model for this study is represented as follows:

MU of EHRs for PHM = f (munificence, uncertainty, interdependence, control factors)

Methodological Limitations

This study may have a threat to internal validity based on extraneous events. It may be possible that an omitted variable bias exists, i.e. a factor which is not considered in this study may be associated with the MU of EHRs for PHM. This study relies on self-reporting of data for organizational and environmental factors. The inaccuracies in the reporting may lead to biased results. However, the AHA Annual Survey Database is considered well-validated and is used extensively for health services research. This study only considers non-specialty, non-critical access, non-federal, acute care hospitals in the U.S. Hence, the results of this study cannot be generalized to the entire population of hospitals in the U.S. Further, although this study strengthens the relationship between cause and effect by lagging the independent variables (i.e. the cause), but it cannot unequivocally establish causality between the organizational and environmental factors and the use of EHRs for PHM. This study only establishes association between the organizational and environmental factors and the MU of EHRs for PHM.

Ethical Considerations

This study does not use any human subjects or patient-level data. The data used in this study is administrative data and does not identify any particular person. Further, this data does not contain any sensitive information such as tax identification number, etc. Hence, this study does not require Institutional Board Review.

Summary of the chapter

This chapter describes the research design used for this study and examines the strengths and limitations of the research design. It also describes the data sources used for this study. The measures identified in Chapter 3 are defined and the measurement of each measure in terms of dependent, independent, and control variables is described. The data analysis plan and the models used for data analysis are described. Further, the methodological limitations of the study are identified and the ethical considerations for this study are explained. The following Chapters 5 and 6 describe and discuss the results of this study.

CHAPTER FIVE: RESULTS

This chapter presents the results of the empirical analyses of this study. The chapter is divided into two sections: descriptive analyses results and multivariate analyses results. The descriptive analyses results section includes the description of the study sample, the comparison of the organizational and environmental characteristics of the study sample and population, the descriptive statistics for the study sample, and the results of the correlation analysis for the independent variables used in this study. The multivariate analyses results section includes the results of four empirical models examining the organizational and environmental factors associated with the MU of EHRs for PHM. The models are:

1. Implementation of MU of EHRs for submission of electronic data to immunization registries
2. Implementation of MU of EHRs for submission of electronic data on reportable laboratory results to public health agencies
3. Implementation of MU of EHRs for submission of electronic syndromic surveillance data to public health agencies
4. Level of MU of EHRs for PHM.

Descriptive Analyses Results

Creation of the Study Sample

The aim of this study was to examine the organizational and environmental correlates of MU of EHRs for PHM by acute care hospitals in the U.S. The study population consisted of all non-critical access hospitals (non-CAH), non-federal, acute care hospitals operating for at least 270 days within the 50 U.S. States and the District of Columbia. The dependent variables were measured in 2014 while the independent variables were measured in 2013 (except stage of implementation of MU of EHRs which was measured in 2014) to represent a one year lag for the independent variables.

This paragraph describes the steps for creation of the study population. The main data source for this study which provides information on hospitals is the AHA Annual Survey Database for the year 2013. In 2013, there were 6,295 total hospitals in the dataset. Only the acute care hospitals were retained in this dataset. The number of hospitals excluded were 1,524 and the number of acute care hospitals that remained in the study population were 4,771. Acute care hospitals that were open and operational for at least 270 days in the reporting period were retained. The number of hospitals excluded were 917 and the number of acute care hospitals open and operational for at least 270 days that were retained were 3,854. Further, only the non-CAH hospitals were retained. The number of hospitals excluded were 1,072 and the number of non-CAH, acute care hospitals open and operational for at least 270 days that were retained were 2,782. Only the non-federal hospitals were retained. The number of hospitals excluded were 65 and the number of non-CAH, non-federal, acute care hospitals open and operational for at least 270 days that were retained were 2,717. Only those hospitals located in the 50 U.S. states and the District of Columbia were retained. The number of hospitals excluded was 11 and the number of non-CAH, non-federal, acute care hospitals open and operational for at least 270 days and located in the 50 U.S. states and the District of Columbia that were retained were 2,706. These 2,706 hospitals comprised the study population.

This paragraph describes the steps for creation of the study sample. The dependent variables were obtained from the CMS MU Stage 1 and Stage 2 files for 2014. Hence, the AHA annual survey database was merged with the CMS MU Stage 1 and Stage 2 data files for the year 2014 using the Medicare Provider Number. Medicare Provider Number is a unique identification number for each unique hospital. After merging these data obtained from AHA 2013 and the CMS MU 2014, 308 hospitals were excluded. The number of hospitals that remained in the study sample were 2,398. Some of the independent variables, i.e. per capita income, rurality, and HHI, were obtained from the AHRF dataset. Hence, the merged dataset containing 2,398 hospitals was merged with the AHRF dataset for the year 2013. After this merge, 37 hospitals were excluded. The study sample was 2,361 after the AHRF data merge. Missing observations and valid values were examined for all the study variables. There were 8 such observations which were excluded from the study sample. The final empirical study sample consisted of 2,353 hospitals. Table 3 summarizes the steps of the creation of the analytical study sample and the number of hospitals at each step.

Table 3: Creation of the Study Sample

Study sample creation steps	Number of hospitals
Total number of hospitals in the AHA database 2013	6,295
Total number of acute care hospitals	4,771
Acute care hospitals which were open and operational for 270 days during the reporting period	3,854
Excluding Critical Access Hospitals (CAH)	2,782
Excluding federal hospitals	2,717
Keeping hospitals which are in the 50 U.S. states and the District of Columbia: Excluding hospitals in U.S. territories (American Samoa, Federal States of Micronesia, Guam, Marshall Islands, Northern Mariana Islands, Palau, Puerto Rico, and Virgin Islands)	**2,706**
Merging with Stage 1 and Stage 2 MU data files	2,398
Merging with AHRF dataset	2,361
Excluding missing observations for study variables and non-valid values	2,353
Final analytical sample of non-federal non-CAH acute care hospitals in the U.S.	**2,353**

Comparison of the Study Population and Sample

For the independent variables obtained from the AHA Annual Survey Database, comparisons were made between the study sample and all non-CAH, non-federal, acute care hospitals in the study population in the AHA Annual Survey Database. Some independent variables (i.e. per capita income – INCOME, Herfindahl-Hirschman Index – HHI, geographic location of the hospital – RURALITY) were obtained from the AHRF dataset. However, AHRF dataset does not have information on individual hospitals. Hence, the AHRF dataset was merged with the AHA Annual Survey Database. For the independent variables obtained from the AHRF dataset, comparisons were made between the study sample and all non-CAH, non-federal, acute care hospitals in the study population in the merged AHA Annual Survey Database and the AHRF dataset.

The study sample is restricted to all the hospitals which reported to CMS on MU of EHRs. The data on dependent variables and the independent variable of stage of implementation of MU (i.e. STAGEDUMMY) is available only for the study sample since this data is obtained from the hospitals' reporting to the CMS. Hence, the dependent variables and STAGEDUMMY were excluded from this comparison.

One sample t-tests were used to compare the continuous variables in the study sample with the study population, while one sample tests of proportion were used to compare the categorical variables in the study sample with the study population. The null hypothesis tested in this comparison was that the sample means or sample proportions of the study sample were equal to the true means or true proportions of the study population. For all the independent variables, there were no statistically significant differences between the study sample and the study population at $p < 0.05$ level. Hence, the study sample was representative of the study population. The results of the comparison of study population and sample are presented in Table 4.

Table 4: Comparison of the Study Sample and the Study Population

Variables from the AHA Annual Survey Database				
Variable	**Population (N = 2,706) Mean (SD) / Frequency (%)**	**Sample (N = 2,353) Mean (SD) / Frequency (%)**	**t-statistic / z-statistic**	**p-value**
Organizational Factors				
BEDS	231.058 (218.793)	235.803 (218.110)	1.0553	0.2914
PAYER	0.705 (0.155)	0.702 (0.123)	-1.1831	0.2369
FORPROFIT	471 (17.41%)	408 (17.34%)	-0.0895	0.9286
PUBLIC	411 (15.19%)	357 (15.17%)	-0.0270	0.9784
SYSTEM	1837 (67.89%)	1583 (67.28%)	-0.6337	0.5262
TEACH	245 (9.05%)	211 (8.97%)	-0.1353	0.8924
Environmental Factor				
LAW	1155 (42.68%)	1003 (42.63%)	-0.0490	0.9609
Variables from the AHRF Dataset				
Variable	**Population (N = 2,663) Mean (SD) / Frequency (%)**	**Sample (N = 2,353) Mean (SD) / Frequency (%)**	**t-statistic / z-statistic**	**p-value**
Environmental Factors				
INCOME	43106.44 (11493.91)	43250.83 (11510.04)	0.6085	0.5429
HHI	0.408 (0.361)	0.403 (0.364)	-0.6663	0.5053
RURALITY	1995 (74.92%)	1769 (75.18%)	0.2910	0.7711

Note: For categorical variables, frequencies and percentages are given only for the category = 1.

Sample Descriptive Characteristics

The distributions of all the variables were examined for skewness and kurtosis and log transformation was performed where appropriate. Size of the hospital (BEDS) was skewed to the right (skewness = 1.99; kurtosis = 10.77) and hence was log transformed to LOG_BEDS (skewness = -0.41; kurtosis = 3.06). Per capita income (INCOME) was also skewed to the right (skewness = 2.61; kurtosis = 16.15) and hence were log transformed to LOG_INCOME (skewness = 0.71; kurtosis = 4.29).

Of the total 2,353 hospitals in the study sample, 1,734 (73.69%) had implemented the MU objective of EHRs on the submission of electronic data to immunization registries, 1,193 (50.7%) had implemented the MU objective of EHRs on the submission of electronic data on reportable laboratory results to public health agencies, and 1,212 (51.51%) had implemented the MU objective of EHRs on the submission of electronic syndromic surveillance data to public health agencies. Among the hospitals in the study sample, 850 (36.12%) had comprehensive level of MU of EHRs for PHM i.e. had implemented all three PHM objectives of MU of EHRs, 296 (12.58%) had moderate level of MU of EHRs for PHM i.e. had implemented two of the three PHM objectives of MU of EHRs, 997 (42.37%) had minimal level of MU of EHRs for PHM i.e. had implemented one of the three PHM objectives of MU of EHRs, and 210 (8.92%) had no MU of EHRs for PHM i.e. did not implement any of the PHM objectives of MU of EHRs.

In the study sample, majority of the hospitals were system members (n = 1,583; 67.28%). Out of the 2,353 hospitals in the study sample, 408 (17.34%) hospitals were for-profit hospitals, 357 (15.17%) were non-federal government hospitals, and the rest were not-for-profit hospitals. Over half of the hospitals (n = 1,003; 57.37%) were located in states where a state policy for public health surveillance was documented. Majority of the hospitals (n = 1,219; 51.81%) were in the Stage 1 of MU implementation of EHRs and less than half of the hospitals (n = 1,134; 48.19%) were in the Stage 2 of MU implementation of EHRs. The mean number of hospital unit beds set up and staffed were 235.80 while the mean of log of number of hospital unit beds set up and staffed was 5.08. The mean public payer mix was 0.70. The mean per capita income of the population in the county was $43250.83 and the mean of log of per capita income of the population in the county was 10.65. The mean Herfindahl-Hirschman Index was 0.40. Few hospitals (n = 211; 8.97%) were teaching hospitals. The majority of the hospitals (n = 1,769; 75.18%) were located in metropolitan areas. Table 5 presents the descriptive statistics of the study sample including the frequencies and percentages for categorical variables and mean, standard deviation, minimum, and maximum for continuous variables.

Table 5: Descriptive Statistics for Study Variables

Variable	Definition	Study Sample (N = 2,353)			
		Frequency (%)	**Mean (S.D.)**	**Minimum**	**Maximum**
Dependent Variables					
IMMUNIZATION	1 = Yes, objective met 0 = No, objective not met	1 = 1,734 (73.69%) 0 = 619 (26.31%)	-	-	-
LABORATORY	1 = Yes, objective met 0 = No, objective not met	1 = 1,193 (50.70 %) 0 = 1,160 (49.30%)	-	-	-
SURVEILLANCE	1 = Yes, objective met 0 = No, objective not met	1 = 1,212 (51.51%) 0 = 1,141 (48.49%)	-	-	-
LEVEL	3 = Comprehensive level of MU of EHRs for PHM 2 = Moderate level of MU of EHRs for PHM 1 = Minimum level of MU of EHRs for PHM 0 = No MU of EHRs for PHM	3 = 850 (36.12%) 2 = 296 (12.58%) 1 = 997 (42.37%) 0 = 210 (8.92%)	-	-	-
Organizational Factors					
SYSTEM	1 = Yes, system member 0 = No, not a system member	1 = 1,583 (67.28%) 0 = 770 (32.72%)	-	-	-
FORPROFIT	1 = Investor owned, for-profit 0 = Otherwise	1 = 408 (17.34%) 0 = 1,945 (82.66%)	-	-	-
PUBLIC	1 = Government, non-federal 0 = Otherwise	1 = 357 (15.17%) 0 = 1,996 (84.83%)	-	-	-
STAGEDUMMY	1 = Stage 2 of MU 0 = Stage 1 of MU	1 = 1,134 (48.19%) 0 = 1,219 (51.81%)	-	-	-

Variable	Definition	Study Sample (N = 2,353)			
		Frequency (%)	**Mean (S.D.)**	**Minimum**	**Maximum**
BEDS	Total number of hospital unit beds staffed and set up	-	235.803 (218.11)	4	2,396
LOG_BEDS	Log (Total number of hospital unit beds staffed and set up)	-	5.075 (0.939)	1.386	7.782
PAYER	(Medicare inpatient days + Medicaid inpatient days) / Total inpatient days	-	0.702 (0.123)	0	1
TEACH	1 = Yes, teaching hospital 0 = No, not a teaching hospital	1 = 211 (8.97%) 0 = 2,142 (91.03%)	-	-	-
Environmental Factors					
INCOME	Per capita personal income of the population in the county	-	43,250.83 (11,510.04)	20,811	121,632
LOG_INCOME	Log (Per capita personal income of the population in the county)	-	10.645 (0.237)	9.943	11.709
HHI	Sum of squared market shares of number of hospital beds staffed and set up	-	0.403 (0.364)	0.002	1
LAW	1 = State policy documented 0 = No state policy documented	1 = 1,003 (42.63%) 0 = 1,350 (57.37%)	-	-	-
RURALITY	1 = Metropolitan 0 = Non-metropolitan	1 = 1,769 (75.18%) 0 = 584 (24.82%)	-	-	-

Note: S.D is standard deviation

Correlation Analysis

A correlation analysis of all the independent variables was conducted to detect multi-collinearity between the independent variables. The standard cut-off point of $r = 0.70$ was used. The correlation coefficient of all the paired variables was lower than 0.70, which indicated a lack of multi-collinearity in the data. Therefore, all the independent variables were included in the multivariate regression analyses. Table 6 summarizes the results of the correlation analysis.

Table 6: Correlation Analysis of Independent Variables

	HHI	PAYER	SYSTEM	TEACH	RURALITY	LAW	FORPROFIT	PUBLIC	LOG_INCOME	LOG_BEDS	STAGEDUMMY
HHI	1										
PAYER	0.1787	1									
SYSTEM	-0.1801	-0.0657	1								
TEACH	-0.2006	-0.1206	0.0002	1							
RURALITY	-0.5806	-0.1855	0.1822	0.1734	1						
LAW	-0.1106	-0.059	0.0242	-0.0179	0.0675	1					
FORPROFIT	-0.082	-0.0351	0.1902	-0.1202	0.0293	0.0252	1				
PUBLIC	0.2015	0.053	-0.3489	0.0497	-0.1848	-0.101	-0.1937	1			
LOG_INCOME	-0.4292	-0.2385	0.0538	0.1942	0.3749	0.1354	-0.0738	-0.1166	1		
LOG_BEDS	-0.3549	-0.0224	0.1203	0.4108	0.4124	-0.0071	-0.1451	-0.0881	0.2429	1	
STAGEDUMMY	-0.0209	0.0126	-0.0143	0.0456	0.0107	0.0148	-0.0823	-0.0333	0.0493	0.1034	1

Multivariate Regression Analyses Results

Multivariate regression analyses were conducted using STATA 14.0 software (StataCorp LP., College Station, TX). The study sample size was 2,353. The analytical sample for this study was hierarchical in nature, i.e. the sample consisted of hospitals nested within states and both hospital level and state level factors were included in the regression analyses. Hence, mixed effects models were used. Three of the four dependent variables, i.e. IMMUNIZATION, LABORATORY, and SURVEILLANCE, represented the implementation of MU objectives of EHRs for PHM. These three variables were binary variables and given the hierarchical nature of the data, mixed effects logistic regression models were appropriate. The fourth dependent variable, i.e. LEVEL, represented the level of MU of EHRs for PHM. This variable was a categorical variable with four categories and given the hierarchical nature of the data, mixed effects multinomial logistic regression model was appropriate. To summarize, mixed effects logistic regression models were used for the dependent variables IMMUNIZATION, LABORATORY, and SURVEILLANCE; and mixed effects multinomial logistic regression model was used for the dependent variable LEVEL.

Model 1: Implementation of MU of EHRs for submission of electronic data to immunization registries

Model 1 examines the organizational and environmental factors associated with the implementation of MU objective of EHRs on the submission of electronic data to immunization registries using a mixed effects logistic regression model. As hypothesized, the odds of submission of electronic data to immunization registries among for-profit hospitals were 2.15 times that of non-profit hospitals ($p < 0.001$). As hypothesized, the odds of submission of electronic data to immunization registries among hospitals that were members of a multi-hospital system were 1.54 times that of hospitals which were non-members of a multi-hospital system ($p < 0.01$). As hypothesized, the odds of submission of electronic data to immunization registries among hospitals in Stage 2 of implementation of MU of EHRs were 8.98 times that of hospitals in Stage 1 of implementation of MU of EHRs ($p < 0.001$). As hypothesized, the odds of submission of electronic data to immunization registries among hospitals located in states with documented public health surveillance laws/policies were 1.93 times that of hospitals located in states without documented public health surveillance laws/policies; however, this association is only marginally significant ($p < 0.10$). Contrary to the hypothesis, the odds of submission of electronic data to immunization registries among hospitals in area with greater HHI, i.e. lower market competition were 1.42 times that of the hospitals in areas with greater market competition; this association is also marginally significant ($p < 0.10$). The control factor of rurality was marginally significant ($p < 0.10$); the odds of submission of electronic data to immunization registries among hospitals located in metropolitan areas were 1.32 times that of the hospitals located in non-metropolitan areas.

The organizational factors - size of the hospital (i.e. LOG_BEDS), government non-federal hospitals (i.e. PUBLIC), and public payer mix (i.e. PAYER) were not statistically significant. The environmental factor – per capita income of the area (i.e. LOG_INCOME) was not statistically significant. The control factor teaching hospitals (i.e. TEACH) was also not statistically significant. The results from this model are presented in Table 7.

Table 7: Parameter Estimates: Implementation of MU of EHRs for Submission of Electronic Data to Immunization Registries

Correlates	Odds Ratio	95% Confidence Interval for Odds Ratio		p-value
		Lower Limit	Upper Limit	
Organizational Factors				
LOG_BEDS	1.010	0.874	1.169	0.888
FORPROFIT (For profit vs not for profit)	2.145	1.519	3.028	0.000***
PUBLIC (Government vs not for profit)	1.236	0.874	1.746	0.230
SYSTEM (System member vs non-system member)	1.537	1.195	1.977	0.001**
PAYER	0.606	0.230	1.598	0.311
STAGEDUMMY (Stage 2 vs stage 1)	8.981	6.861	11.756	0.000***
TEACH (Teaching vs non-teaching)	1.290	0.831	2.003	0.256
Environmental Factors				
HHI	1.419	0.941	2.141	$0.095^{\#}$
LOG_INCOME	1.241	0.696	2.213	0.464
LAW (States with laws vs states without laws)	1.927	0.885	4.199	$0.099^{\#}$
RURALITY (Metropolitan vs non-metropolitan)	1.321	0.955	1.828	$0.093^{\#}$
Constant	0.058	0.000	32.874	0.379
Sample Size: N = 2,353				
$^{\#}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$				

Model 2: Implementation of MU of EHRs for submission of electronic data on reportable laboratory results to public health agencies

Model 2 examines the organizational and environmental factors associated with the implementation of the MU objective of EHRs on the submission of electronic data on reportable laboratory results to public health agencies, using a mixed effects logistic regression model. As hypothesized, the odds of submission of electronic data on reportable laboratory results among larger hospitals were greater ($p < 0.05$). With each percent increase in LOG_BEDS, the odds of submission of electronic data on reportable laboratory results among hospitals multiplied by 1.24. As hypothesized, the odds of submission of electronic data on reportable laboratory results among hospitals in Stage 2 of implementation of MU of EHRs were 67.88 times that of the hospitals in Stage 1 of implementation of MU of EHRs ($p < 0.001$). As hypothesized, the odds of submission of electronic data on reportable laboratory results among hospitals in areas of greater community wealth were higher; however, this association was only marginally significant ($p < 0.10$). With each percent increase in LOG_INCOME, the odds of submission of electronic data on reportable laboratory results multiplied by 1.85.

The organizational factors – for-profit hospitals (i.e. FORPROFIT), government non-federal hospitals (i.e. PUBLIC), system membership (i.e. SYSTEM), and public payer mix (i.e. PAYER) were not statistically significant. The environmental factors– market competition (i.e. HHI) and state policies/laws (i.e. LAW) were not statistically significant. The control factors - teaching hospitals (i.e. TEACH) and geographic location of the hospital (i.e. RURALITY) were also not statistically significant. The results from this model are presented in Table 8.

Table 8: Parameter Estimates: Implementation of MU of EHRs for Submission of Electronic Data on Reportable Laboratory Results to Public Health Agencies

Correlates	Odds Ratio	95% Confidence Interval for Odds Ratio		p-value
		Lower Limit	Upper Limit	
Organizational Factors				
LOG_BEDS	1.243	1.053	1.467	0.010*
FORPROFIT (For profit vs not for profit)	0.763	0.522	1.115	0.162
PUBLIC (Government vs not for profit)	0.861	0.583	1.273	0.454
SYSTEM (System member vs non-system member)	1.177	0.875	1.583	0.282
PAYER	0.530	0.175	1.609	0.262
STAGEDUMMY (Stage 2 vs stage 1)	67.875	49.915	92.296	0.000***
TEACH (Teaching vs non-teaching)	0.862	0.534	1.392	0.543
Environmental Factors				
HHI	0.826	0.513	1.329	0.430
LOG_INCOME	1.846	0.969	3.518	0.062#
LAW (States with laws vs states without laws)	0.862	0.400	1.858	0.705
RURALITY (Metropolitan vs non-metropolitan)	1.170	0.799	1.714	0.419
Constant	0.000	0.000	0.113	0.010
Sample Size: N = 2,353				
#p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001				

Model 3: Implementation of MU of EHRs for submission of electronic syndromic surveillance data to public health agencies

Model 3 examines the organizational and environmental factors associated with the implementation of MU objective of EHRs on the submission of electronic syndromic surveillance data to public health agencies using a mixed effects logistic regression model. As hypothesized, the odds of submission of electronic syndromic surveillance data was higher among larger hospitals ($p < 0.001$). With each percent increase in LOG_BEDS, the odds of submission of electronic syndromic surveillance data multiplied by 1.33. As hypothesized, the odds of submission of electronic syndromic surveillance data among hospitals in Stage 2 of implementation of MU of EHRs were 29.5 times that of the hospitals in Stage 1 of implementation of MU of EHRs ($p < 0.001$). As hypothesized, the odds of submission of electronic syndromic surveillance data among hospitals in areas of greater HHI i.e. areas of lower market competition were lower than that of the hospitals in areas of greater market competition ($p < 0.001$). With each unit increase in HHI, the odds of submission of electronic syndromic surveillance data mutliplied by 0.61 times. Contrary to the hypothesis, the odds of submission of electronic syndromic surveillance data among for-profit hospitals were 0.53 times that of the non-profit hospitals ($p < 0.001$). The control factor – teaching hospitals were negatively associated with implementation of MU of EHRs for submission of surveillance data. The odds of submission of electronic syndromic surveillance data among teaching hospitals were 0.49 times that of the non-teaching hospitals.

The organizational factors – government non-federal hospitals (i.e. PUBLIC), system membership (i.e. SYSTEM), and public payer mix (i.e. PAYER) were not statistically significant. Further, the environmental factors – community wealth (i.e. LOG_INCOME) and state policies/laws (i.e. LAW) were not statistically significant. The control factor - geographic location of the hospital (i.e. RURALITY) was also not statistically significant. The results from this model are presented in Table 9.

Table 9: Parameter Estimates: Implementation of MU of EHRs for Submission of Electronic Syndromic Surveillance Data to Public Health Agencies

Correlates	Odds Ratio	95% Confidence Interval for Odds Ratio		p-value
		Lower Limit	Upper Limit	
Organizational Factors				
LOG_BEDS	1.332	1.136	1.562	0.000***
FORPROFIT (For profit vs not for profit)	0.528	0.374	0.747	0.000***
PUBLIC (Government vs not for profit)	0.878	0.611	1.263	0.485
SYSTEM (System member vs non-system member)	0.985	0.747	1.298	0.913
PAYER	0.850	0.294	2.457	0.765
STAGEDUMMY (Stage 2 vs stage 1)	29.499	22.376	38.888	0.000***
TEACH (Teaching vs non-teaching)	0.488	0.310	0.769	0.002**
Environmental Factors				
HHI	0.610	0.395	0.941	0.026*
LOG_INCOME	0.691	0.374	1.278	0.239
LAW (States with laws vs states without laws)	1.500	0.494	4.553	0.475
RURALITY (Metropolitan vs non-metropolitan)	0.756	0.529	1.079	0.123
Constant	4.223	0.005	3588.874	0.675
Sample Size: N = 2,353				
$^{\#}p < 0.10$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$				

Model 4: Level of MU of EHRs for PHM

Model 4 examines the organizational and environmental factors associated with the level of MU of EHRs for PHM, using a mixed effects multinomial logistic regression model. As hypothesized, the odds of higher level of MU of EHRs for PHM for larger hospitals were higher ($p < 0.01$). With one percent increase in LOG_BEDS, the odds of comprehensive level of MU of EHRs for PHM are multiplied by 1.53 times. The stage of implementation of MU of EHRs was significantly and positively associated with all levels of MU of EHRs for PHM ($p < 0.001$). As hypothesized, the odds of comprehensive level of MU of EHRs for PHM among hospitals in Stage 2 of implementation of MU of EHRs were 94.07 times that of the hospitals in Stage 1 of implementation of MU of EHRs; the odds of moderate level of MU of EHRs for PHM among hospitals in Stage 2 of implementation of MU of EHRs were 8.92 times that of the hospitals in Stage 1 of implementation of MU of EHRs. However contrary to the hypothesis, the odds of minimum level of MU of EHRs for PHM among hospitals in Stage 2 of implementation of MU of EHRs were 0.2 times that of the hospitals in Stage 1 of implementation of MU of EHRs. As hypothesized, for-profit ownership of hospitals (i.e. FORPROFIT) was positively associated with minimum and moderate use of EHRs for PHM; however, this association was only marginally significantly ($p < 0.10$). The odds of minimum level of MU of EHRs for PHM among for-profit hospitals were 1.60 times and the odds of moderate level of MU of EHRs for PHM among for-profit hospitals were 1.63 times that of the non-profit hospitals. As hypothesized, hospitals located in states with laws/policies on public health surveillance were positively associated with higher level of MU of EHRs; this association was only marginally significant ($p < 0.10$). The odds of minimum level of MU of EHRs for PHM among hospitals located in states with laws/policies on public health surveillance were 2.11 times and the odds of moderate level of MU of EHRs for PHM among hospitals located in states with laws/policies on public health surveillance were 2.24 times that of the hospitals in states without laws/policies on public health surveillance.

The organizational factors – government non-federal hospitals (i.e. PUBLIC), system membership (i.e. SYSTEM), and public payer mix (i.e. PAYER) were not statistically significant. The environmental factors – market competition (i.e. HHI) and community wealth (i.e. LOG_INCOME) were also not statistically significant. The control factors – teaching hospital (i.e. TEACH) and geographic location of the hospital (i.e. RURALITY) were not statistically significant. The results from this model are presented in Table 10.

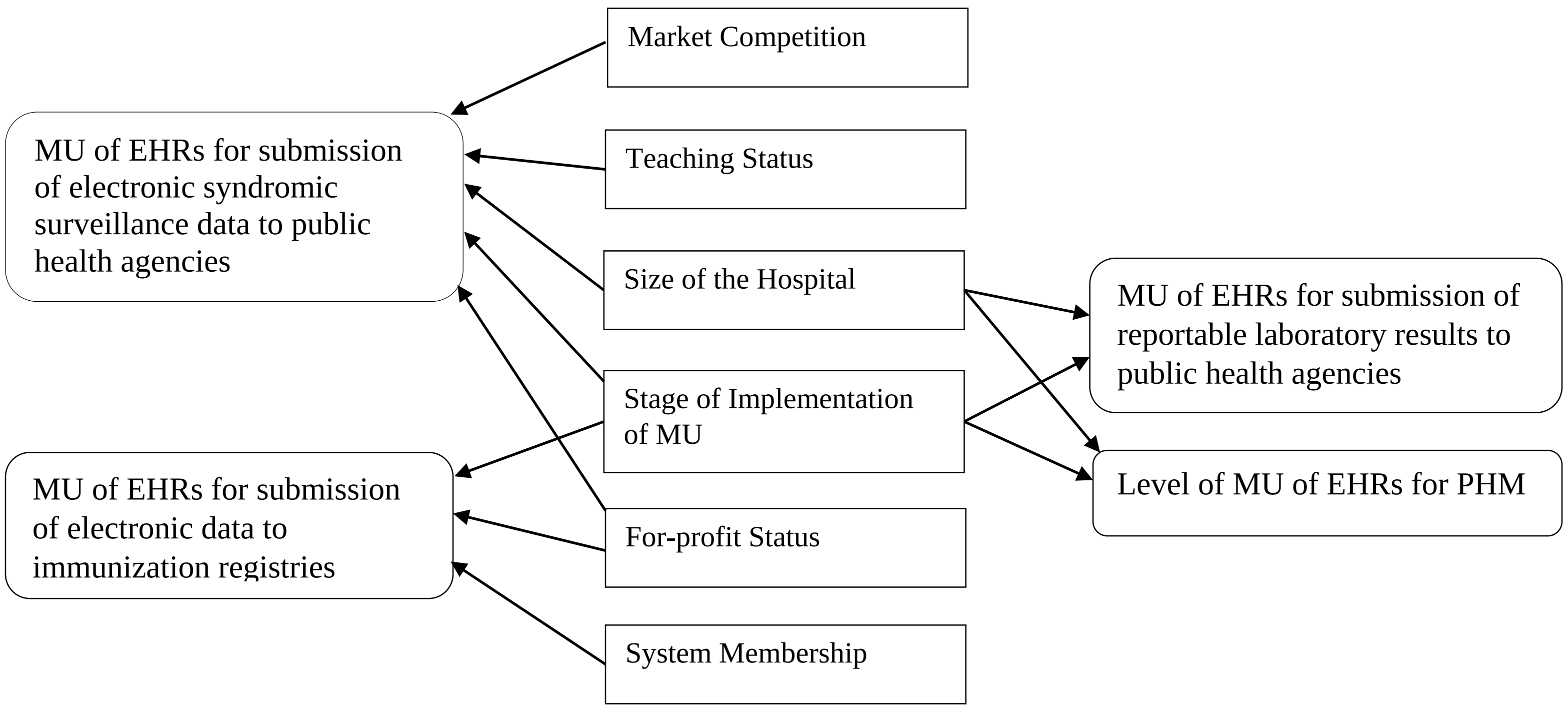
Table 10: Parameter Estimates: Level of MU of EHRs for PHM

Correlates	**Level of MU**	**Odds Ratio**	**95% Confidence Interval for Odds Ratio**		**p-value**
			Lower Limit	**Upper Limit**	
Organizational Factors					
LOG_BEDS	Minimum	1.050	0.854	1.291	0.642
	Moderate	1.136	0.884	1.460	0.319
	Comprehensive	1.533	1.196	1.965	0.001**
FORPROFIT (For profit vs not for profit)	Minimum	1.598	0.994	2.570	0.053#
	Moderate	1.630	0.913	2.908	0.098#
	Comprehensive	0.989	0.550	1.780	0.972
PUBLIC (Government vs not for profit)	Minimum	1.197	0.732	1.958	0.473
	Moderate	1.077	0.593	1.958	0.807
	Comprehensive	1.036	0.577	1.862	0.905
SYSTEM (System member vs non-system member)	Minimum	1.062	0.728	1.550	0.756
	Moderate	1.097	0.694	1.733	0.693
	Comprehensive	1.457	0.931	2.280	0.100
PAYER	Minimum	0.488	0.121	1.976	0.315
	Moderate	0.312	0.058	1.688	0.176
	Comprehensive	0.451	0.082	2.496	0.362
STAGEDUMMY (Stage 2 vs stage 1)	Minimum	0.203	0.130	0.319	0.000***
	Moderate	8.924	5.743	13.868	0.000***
	Comprehensive	94.070	57.125	154.909	0.000***

Correlates	Level of MU	Odds Ratio	95% Confidence Interval for Odds Ratio		p-value
			Lower Limit	Upper Limit	
TEACH (Teaching vs non-teaching)	Minimum	0.918	0.473	1.781	0.801
	Moderate	0.938	0.431	2.044	0.873
	Comprehensive	0.572	0.269	1.218	0.147
Environmental Factors					
HHI	Minimum	1.386	0.778	2.471	0.268
	Moderate	1.326	0.654	2.689	0.434
	Comprehensive	0.806	0.404	1.609	0.540
LOG_INCOME	Minimum	1.353	0.573	3.191	0.490
	Moderate	2.301	0.841	6.298	0.105
	Comprehensive	1.075	0.391	2.958	0.889
LAW (States with laws vs states without laws)	Minimum	2.111	0.920	4.846	$0.078^{\#}$
	Moderate	2.236	0.945	5.287	$0.067^{\#}$
	Comprehensive	1.840	0.781	4.335	0.163
RURALITY (Metropolitan vs non-metropolitan)	Minimum	0.795	0.503	1.255	0.324
	Moderate	0.843	0.477	1.491	0.557
	Comprehensive	1.195	0.685	2.086	0.530
Constant	Minimum	0.242	0.000	2798.313	0.766
	Moderate	0.000	0.000	3.998	0.087
	Comprehensive	0.013	0.000	840.965	0.445
Sample Size: N = 2,353					
$^{\#}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$					

A summary of the results of the empirical analyses are illustrated in Figure 3.

Figure 3: Summary of the Empirical Results



Summary of the Chapter

This chapter presented the results of the descriptive and multivariate regression analyses. The study sample was representative of the study population. The multivariate regression analyses showed that the independent variables: for-profit ownership of hospitals, system membership, and stage of MU implementation were significantly associated with the implementation of EHRs for submission of electronic data to immunization registries. The size of the hospital and the stage of MU implementation were significantly associated with the implementation of EHRs for submission of electronic data on reportable laboratory results to public health agencies. The size of the hospital, for-profit ownership of hospitals, the stage of MU implementation, teaching status, and market competition were significantly associated with the implementation of EHRs for submission of electronic syndromic surveillance data to public health agencies. Finally, the size of the hospital and stage of MU implementation were significantly associated with the level of MU of EHRs for PHM.

In the next and final chapter, Chapter 6, a summary of the results of descriptive statistics and hypothesis testing through multivariate analyses are presented. The chapter also provides the interpretation of the results and a discussion of the study implications for future policy, research and practice. Chapter 6 also presents a discussion of the limitations of this study and opportunities for future research.

CHAPTER SIX: DISCUSSION

The aim of this study was to examine the organizational and environmental factors associated with the implementation of MU of EHRs for PHM. There are three PHM objectives for the MU of EHRs: 1. Submission of electronic data to immunization registries, 2. Submission of electronic data on reportable laboratory results to public health agencies, and 3. Submission of electronic syndromic surveillance data to public health agencies. Based on these three PHM objectives of MU of EHRs, two research questions were posed in this study:

1. What are the organizational and environmental factors associated with the implementation of the PHM objectives of MU of EHRs in acute care hospitals in the U.S.?
2. What are the organizational and environmental factors associated with the level of MU of EHRs for PHM in acute care hospitals in the U.S.?

For the first research question, this study examined the factors associated with each of the PHM objectives mentioned above. For the second research question, this study examined level of MU of EHRs for PHM which was a composite measure created using the three PHM objectives mentioned above. This study derived its conceptual framework from the resource dependency theory and the central premise of this study was: organizational and environmental factors will be associated with the implementation of each of the PHM objectives of MU of EHRs as well as with the higher level of MU of EHRs for PHM. The organizational factors examined in this study were: size of the hospital, system membership, ownership control of the hospital, public payer mix of the hospital, and stage of MU implementation of EHRs. The environmental factors included in this study were: degree of market competition, community wealth in the hospital market area, and the documentation of state laws in the state of the hospital. This study included an organizational control variable of teaching status and an environmental control variable of the geographic (rural-urban) location of the hospital.

Specific hypotheses for this study were based on the three constructs of resource dependency theory: munificence, uncertainty, and interdependence. It was proposed that hospital size, membership of multi-hospital system, and community wealth which represented munificence, market competition which represented uncertainty and ownership control, public payer mix, state laws, and stage of MU implementation of EHRs which represented interdependence would be associated with the implementation of PHM objectives of MU of EHRs and higher level of MU of EHRs for PHM. Specifically, larger hospital size, being a system member, greater community wealth, greater market competition, being a for-profit or a public hospital (as compared to non-profit hospitals), having a higher public payer mix, operating in a state with documented health information technology laws, and being in the stage 2 of MU implementation of EHRs would be positively associated with the implementation of PHM objectives of MU of EHRs and the higher level of MU of EHRs for PHM.

To test these hypotheses, data were obtained from four secondary administrative data sources: the AHA Annual Survey Database maintained by the American Hospital Association, CMS MU Stage 1 and Stage 2 data files maintained by the CMS, the AHRF database maintained by the U.S. Health Resources and Services Administration, and the state HIT policy levers compendium maintained by the ONC. The independent variables for this study were obtained from the AHA annual survey database 2013, AHRF database for the year 2013, state HIT policy lever compendium 2011-2013, and CMS Stage 1 and Stage 2 MU files for the year 2014. The dependent variables for this study were obtained from the CMS Stage 1 and Stage 2 MU data files for the year 2014. All independent variables except one (stage of implementation of MU) were lagged by one year in this study. Only non-CAH, non-federal acute care hospitals in the 50 U.S. States and the District of Columbia which were open and operational for at least 270 days were included in the study population. After merging all the datasets and retaining only those hospitals with non-missing and valid values, the final study sample included 2,353 hospitals.

The ensuing parts of this chapter present a summary of the descriptive and multivariate analyses results and the interpretation of these results. Further, the implications of this study for theory-based research, practice, and policy are discussed. The limitations of this study and future research directions are also presented further in this chapter.

Summary and Interpretation of the Descriptive Analyses

Descriptive analyses of the study variables were conducted by calculating frequencies and percentages for categorical variables and mean, standard deviation, minimum, and maximum for continuous variables. Correlation analysis was conducted to examine multi-collinearity between the independent variables of this study. The correlation analysis showed a lack of multi-collinearity between the independent variables. Hence all the independent variables were included in the multivariate analyses. A comparison of the study sample with the study population revealed no statistically significant differences between the two groups. Hence, the study sample was representative of the study population.

Summary and Interpretation of Hypotheses Testing

The ensuing paragraphs discuss the interpretation of the hypotheses that were proposed in Chapter 3 and the results of the empirical models presented in Chapter 5. The MU of EHRs for PHM was operationalized through four different measures: 1. Implementation of MU of EHRs for submission of electronic data to immunization registries (IMMUNIZATION), 2. Implementation of MU of EHRs for submission of electronic data on reportable laboratory results to public health agencies (LABORATORY), 3. Implementation of MU of EHRs for submission of electronic syndromic surveillance data to public health agencies (SURVEILLANCE), and 4. Level of MU of EHRs for PHM (LEVEL). The following paragraphs will elaborate the results based on these four measures of MU of EHRs for PHM.

H1a: All else being equal, larger acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to smaller acute care hospitals.

H1b: All else being equal, larger acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to smaller acute care hospitals.

Hypotheses 1a and 1b proposed that the hospital size would be positively associated with the MU of EHRs for PHM. Thus, larger hospitals are expected to be more likely to implement the three PHM objectives of MU of EHRs. Larger hospitals are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, larger hospitals are expected to have comprehensive, moderate, or minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The results of this study support hypothesis 1a for the MU objectives of submission of electronic data on reportable laboratory results to public health agencies (i.e. LABORATORY) and submission of electronic syndromic surveillance data to public health agencies (i.e. SURVEILLANCE). Size of the hospital was positively and significantly associated with LABORATORY and SURVEILLANCE ($p < 0.05$). The size of the hospital was not significantly associated with the submission of electronic data to immunization registries (i.e. IMMUNIZATION) at the $p < 0.05$ level. The results of this study also support the hypothesis 1b for comprehensive level of MU of EHRs for PHM. Size of the hospital was positively and significantly associated with the comprehensive level of MU of EHRs for PHM. The size of the hospital was not significantly associated with moderate or the minimum level of MU of EHRs for PHM at the $p < 0.05$ level. Although IMMUNIZATION, moderate level of MU of EHRs for PHM, and minimum level of MU of EHRs for PHM were not statistically significant, the positive sign of the coefficient suggests their relationship with the size of the hospital is as hypothesized.

Previous literature supports this finding that larger hospitals are more likely to adopt innovations such as EHRs (Zhang et al., 2013; Burke et al., 2002; Wang et al., 2005; Kazley & Ozcan, 2007; Furukawa et al., 2008; Parente & Van Horn, 2006; Jha, DesRoches, Kralovec, & Joshi, 2010; Jha et al., 2009b; Diana et al., 2015; DesRoches et al., 2013). Table 11 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 1a and 1b.

Table 11: Confirmation of Hypotheses 1a and 1b and the Direction of Coefficients (Organizational Factor: Size of the Hospital)

Model	Level of Use	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.888	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Positive	0.010	Yes
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Positive	0.000	Yes
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.642	No
	Moderate	Positive	Positive	0.319	No
	Comprehensive	Positive	Positive	0.001	Yes

H2a: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are not members of multi-hospital system.

H2b: All else being equal, acute care hospitals that are members of multi-hospital system are more likely to have higher level of MU of EHRs for PHM, as compared to those that are not members of multi-hospital system.

Hypotheses 2a and 2b proposed that membership in a multi-hospital system would be positively associated with the MU of EHRs for PHM. Thus, hospitals which are system members are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals which are system members are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals which are system members are expected to have comprehensive, moderate, or minimum level of MU of EHRs for PHM. Hence, the expected sign of coefficient for these dependent variables is positive.

The findings of this study support hypothesis 2a for the MU objective of submission of electronic data to immunization registries (i.e. IMMUNIZATION). System membership was found to be positively and significantly associated with IMMUNIZATION ($p < 0.01$). System membership was not significantly associated with any of the other dependent variables at the $p < 0.05$ level; however, the positive sign of the coefficient for LABORATORY, comprehensive level of MU, moderate level of MU, and minimum level of MU suggests their relationship with the system membership as hypothesized. The relationship between SURVEILLANCE and system membership is contrary to the hypothesis (SURVEILLANCE has negative sign of the coefficient for system membership) but not statistically significant.

Members of a multi-hospital system have more regional power and reduced competition in the area (Bai & Anderson, 2016; Melnick & Keeler, 2007; Capps & Dranove, 2004; Starkweather & Carman, 1987). This power may help the hospitals to acquire more resources from the environment. The abundance of resources may explain the positive significant association between system membership and IMMUNIZATION. It also supports the positive association with LABORATORY and comprehensive, moderate, and minimum level of MU of EHRs for PHM. Table 12 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 2a and 2b.

Table 12: Confirmation of Hypotheses 2a and 2b and the Direction of Coefficients (Organizational Factor: System Membership)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.001	Yes
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Positive	0.282	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Negative	0.913	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.756	No
	Moderate	Positive	Positive	0.693	No
	Comprehensive	Positive	Positive	0.100	No

H3a: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to implement the PHM objectives of MU of EHRs, as compared to those located in the areas of lower community wealth.

H3b: All else being equal, acute care hospitals located in areas of greater community wealth are more likely to have higher level of MU of EHRs for PHM, as compared to those located in the areas of lower community wealth.

Hypotheses 3a and 3b proposed that higher community wealth would be positively associated with the MU of EHRs for PHM. Thus, hospitals in areas of greater community wealth are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals in areas of greater community wealth are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals in areas of greater community wealth are expected to have comprehensive, moderate, or minimum level of MU of EHRs for PHM. Hence, the expected sign of coefficient for these dependent variables is positive.

The findings of this study do not support hypotheses 3a and 3b for any of the dependent variables. The rationale behind these hypotheses was that hospitals operating in areas of greater community wealth have access to a higher-paying patient population base which reflects the availability of resources for the hospital and would hence they would be more likely to implement MU of EHRs for PHM to attract these patients. However, it is possible that the patients in the market area access the hospital in their community regardless of the innovations implemented by the hospitals. Further, the MU of EHRs for PHM requires the submission of data to public health agencies. These objectives do not require patient interaction with EHRs. Hence it is possible that the patients are unaware about the PHM objectives being implemented by the hospital and are thus indifferent to the implementation of EHRs for PHM. Consequently, the MU of EHRs for PHM may not have any effect on attracting these higher-paying patient populations. Previous studies have also noted that organizational characteristics are the key determinants of strategic behavior and environmental factors play a secondary role in the organization's strategic behavior (Bigelow & Mahon, 1988; Ginn & Young, 1992). A study by Kazley & Ozcan (2007) investigating the organizational and environmental factors associated with the MU of EHRs also did not find any significant associations of MU of EHRs with per capita income. Table 13 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 3a and 3b.

Table 13: Confirmation of Hypotheses 3a and 3b and the Direction of Coefficients (Environmental Factor: Community Wealth)

Model	Level of Use	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.464	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Positive	0.062	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Negative	0.239	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.490	No
	Moderate	Positive	Positive	0.105	No
	Comprehensive	Positive	Positive	0.889	No

H4a: All else being equal, acute care hospitals located in more competitive markets are more likely to implement the PHM objectives of MU of EHRs, as compared to those located in lesser competitive markets.

H4b: All else being equal, acute care hospitals located in more competitive markets are more likely to have higher level of MU of EHRs for PHM, as compared to those located in lesser competitive markets.

Hypotheses 4a and 4b proposed that the degree of market competition would be positively associated with the MU of EHRs for PHM. Thus, the hospitals in areas of greater market competition are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals in areas of greater market competition are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals in areas of greater market competition are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The findings of this study support the hypothesis 4a for PHM objective of submission of electronic syndromic surveillance data to public health agencies (i.e. SURVEILLANCE). Market competition is positively and significantly associated with SURVEILLANCE ($p < 0.05$). However, market competition was not significantly associated with the remaining measures of the dependent variables at the $p < 0.05$ level. Hospitals in an area with greater market competition are more likely to compete with each other. In such areas of greater market competition, hospitals are more likely to implement more sophisticated technology to maintain a competitive edge. Prior to the HITECH Act, local agencies had set up registries and hence EHRs have been used in the past (i.e. before the HITECH Act) for immunization data and laboratory results data. Most of the public health agencies have started the collection of surveillance data after the HITECH Act. Public health agencies had previously lacked the infrastructure to receive the surveillance data and the funding through the HITECH Act has helped these public health agencies to develop health information exchanges to receive the surveillance data (Paul et al., 2015; Wu et al., 2014). Since, the use of EHRs for syndromic surveillance is a relatively recent development, it could be considered as a more sophisticated use of EHRs. Hence, it is likely that the hospitals in areas of greater market competition are more likely to implement EHRs for submission of electronic syndromic surveillance data to the public health agencies.

Table 14 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 4a and 4b.

Table 14: Confirmation of Hypotheses 4a and 4b and the Direction of Coefficients (Environmental Factor: Market Competition)

Model	Level of Use	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Negative	0.095	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Positive	0.430	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Positive	0.026	Yes
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Negative	0.268	No
	Moderate	Positive	Negative	0.434	No
	Comprehensive	Positive	Positive	0.540	No

H5a: All else being equal, for-profit acute care hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to not-for-profit acute care hospitals

H5b: All else being equal, for-profit acute care hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to not-for-profit acute care hospitals

Hypotheses 5a and 5b proposed that for-profit ownership control of the hospital would be positively associated with the MU of EHRs for PHM. Thus, for-profit hospitals are expected to be more likely to implement the three PHM objectives of MU of EHRs. For-profit hospitals are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, for-profit hospitals are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

This study provides mixed evidence for the for-profit status and the MU of EHRs for PHM. The findings of this study support the hypothesis H5a only for the PHM objective of submission of electronic data to immunization registries (i.e. IMMUNIZATION). For-profit ownership of hospitals was positively and significantly associated with IMMUNIZATION ($p < 0.001$). Contrary to the hypothesis, this study found that for-profit ownership was negatively and significantly associated with SURVEILLANCE ($p < 0.001$). Literature also shows mixed findings for the organizational factor of ownership. Some studies have found that for-profit hospitals are more likely to adopt EHRs (Zhang et al., 2013; Taylor et al., 2005; Amarasingham et al., 2008; Diana et al., 2015) which supports the finding of this study for the dependent variable IMMUNIZATION. While a study by Furukawa et al. (2008) which found that not-for-profit hospitals were more likely to adopt EHRs than for-profit hospitals supports the finding of this study for the dependent variable SURVEILLANCE. There were no significant associations of for-profit status with LABORATORY and LEVEL.

The differences in for-profit and non-profit hospitals lies in their mission. For-profit hospitals operate to generate more return on investment for their investors (Greenlick, 1988) while non-profit hospitals place greater emphasis on providing care to their communities which could be uncompensated and charitable (Kim& Thompson, 2012). EHRs are expensive to implement (Miller & Sim, 2004; Simon et al., 2007; Jha et al., 2009b; Abramson et al., 2012) and maintain (Simon et al., 2007; Jha et al., 2009b; Abramson et al., 2012) while providing uncertain financial benefits (Miller & Sim, 2004). The financial burden of implementation of EHRs falls on the hospitals while patients and the payers reap the benefits of the EHRs (Hillestad et al., 2005).

Previous studies have noted that the clinical reminders for immunizations based on the immunization data captured in the EHRs has led to an increase in the number of vaccinations and significantly improved the vaccination rates (Fiks, Grundmeier, Biggs, Localio & Alessandrini, 2007; Gill, Ewen & Nsereko, 2001). For-profit hospitals which are more focused on profits may be more likely to encourage the use of EHRs to capture and submit immunization data since it may cause an increase in the services provided by the hospital and thus their profits. Contrary to this, capturing surveillance data and submitting it to the public health agencies has no monetary return on investment for the for-profit hospitals. Hence, the for-profit hospitals may be less likely to implement EHRs for submission of syndromic surveillance data. However, non-profit hospitals are required to conduct community health needs assessments as a result of the PPACA (Association of State and Territorial Health Officials, n.d.). Using EHRs to capture and submit electronic syndromic surveillance data can also help the non-profit hospitals to collect data necessary for the community health needs assessment (Dixon et al., 2016). Further, non-profit hospitals provide uncompensated or charitable care owing to their tax-exempt status. Surveillance data can help the hospitals to identify and target the vulnerable populations in their communities for preventive services or disease management services which could reduce the amount of uncompensated or charitable care provided by the non-profit hospitals. Hence, non-profit hospitals may be more likely to use EHRs for submission of electronic syndromic surveillance data to the public health agencies. Table 15 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 5a and 5b.

Table 15: Confirmation of Hypotheses 5a and 5b and the Direction of Coefficients (Organizational Factor: For-profit Ownership)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.000	Yes
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Negative	0.162	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Negative	0.000	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.053	No
	Moderate	Positive	Positive	0.098	No
	Comprehensive	Positive	Negative	0.972	No

H6a: All else being equal, government hospitals are more likely to implement the PHM objectives of MU of EHRs, as compared to the not-for-profit acute care hospitals.

H6b: All else being equal, government hospitals are more likely to have higher level of MU of EHRs for PHM, as compared to the not-for-profit acute care hospitals.

Hypotheses 6a and 6b proposed that public ownership control of the hospital would be positively associated with the MU of EHRs for PHM. Thus, government non-federal hospitals are expected to be more likely to implement the three PHM objectives of MU of EHRs. Government non-federal hospitals are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, government non-federal hospitals are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The findings of this study do not support hypotheses H6a and H6b for any of the dependent variables. Government non-federal hospitals often have the sickest patients and have the lowest profit margin (Cutler et al., 2005). These hospitals are more likely to implement other objectives of MU of EHRs such as computerized physician order entry system which could improve their patient outcomes (Cutler et al. 2005). Hence it is possible that the government non-federal hospitals which are operating under lower profit margins may choose to implement MU objectives of EHRs which could help to improve patient outcomes such as computerized physician order entry system as opposed to PHM objectives which may not have a direct demonstrated impact on their patient outcomes.

Table 16 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 6a and 6b.

Table 16: Confirmation of Hypotheses 6a and 6b and the Direction of Coefficients (Organizational Factor: Non-federal, Government Ownership)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.230	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Negative	0.454	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Negative	0.485	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.473	No
	Moderate	Positive	Positive	0.807	No
	Comprehensive	Positive	Positive	0.905	No

H7a: All else being equal, acute care hospitals that have a higher public payer mix are more likely to implement the PHM objectives of MU of EHRs, as compared to those that have a lower public payer mix.

H7b: All else being equal, acute care hospitals that have a higher public payer mix are more likely to have higher level of MU of EHRs for PHM, as compared to those that have a lower public payer mix.

Hypotheses 7a and 7b proposed that higher public payer mix of the hospital would be positively associated with the MU of EHRs for PHM. Thus, hospitals that have a higher public payer mix are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals with a higher public payer mix are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals with a higher public payer mix are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The findings of this study do not support hypotheses 7a and 7b for any of the dependent variables. Public payers such as Medicare and Medicaid reimburse hospitals at lower rates than private insurers (Zinn et al., 1997). Hospitals with higher public payer mix, although more dependent on CMS for their reimbursement, may have lower revenue to invest into expensive innovation such as EHRs, owing to their lower reimbursement rates. Hence, hospitals with higher public payer mix may be less motivated to implement MU of EHRs for PHM. The negative sign of coefficient, although not statistically significant, suggests this relationship. Table 17 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 7a and 7b.

Table 17: Confirmation of Hypotheses 7a and 7b and the Direction of Coefficients (Environmental Factor: Public-payer Mix)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Negative	0.311	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Negative	0.262	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Negative	0.765	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Negative	0.315	No
	Moderate	Positive	Negative	0.176	No
	Comprehensive	Positive	Negative	0.362	No

H8a: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to implement PHM objectives of MU of EHRs, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

H8b: All else being equal, acute care hospitals that are in the Stage 2 of implementation of MU of EHRs are more likely to have a higher level of MU of EHRs for PHM, as compared to those that are in the Stage 1 of implementation of MU of EHRs.

Hypotheses 8a and 8b proposed that the stage of implementation of MU of EHRs would be positively associated with the MU of EHRs for PHM. Thus, hospitals which are in the Stage 2 of MU implementation of EHRs are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals which are in the Stage 2 of MU implementation of EHRs are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals which are in the Stage 2 of MU implementation of EHRs are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The findings of this study support hypotheses 8a and 8b for the PHM objectives of submission of electronic data to immunization registries (i.e. IMMUNIZATION), submission of electronic data on reportable laboratory results to public health agencies (i.e. LABORATORY), submission of electronic syndromic surveillance data to public health agencies (i.e. SURVEILLANCE), and the comprehensive and moderate level of MU of EHRs for PHM (i.e. LEVEL). Stage 2 of implementation of MU of EHRs is positively and significantly associated with IMMUNIZATION, SURVEILLANCE, LABORATORY, and the comprehensive and moderate level of MU of EHRs for PHM ($p < 0.001$). Contrary to the hypothesis, the Stage 2 of implementation of MU of EHRs is negatively and significantly associated with minimum level of MU of EHRs for PHM ($p < 0.001$).

The EHRs incentives program mandates that hospitals which are in Stage 2 of implementation of MU of EHRs must implement the three PHM objectives unless they are eligible to claim exclusion (CMS, 2014 July). Since hospitals are dependent on the EHRs incentives program for funding their EHRs, they are more likely to comply with the mandate. According to the findings of this study, this mandate is successful in achieving the implementation of PHM objectives of MU of EHRs. Further, the mandate is also successful in achieving a higher level of MU of EHRs for PHM. The hospitals which are in Stage 2 of implementation of MU of EHRs may have implemented all three PHM objectives of MU of EHRs due to the mandate and thus have achieved a comprehensive or moderate level of MU of EHRs for PHM to maintain the funding from the EHRs incentives program. Further, the EHRs incentives program mandates that the hospitals which are in the Stage 1 of implementation of MU of EHRs must implement at least one of the three PHM objectives of MU of EHRs (CMS, 2014 July). Hence, hospitals in Stage 1 of implementation of MU of EHRs are more likely to implement one objective thus having a minimum level of MU of EHRs for PHM as compared to the hospitals in Stage 2 of implementation of MU of EHRs which are mandated to implement all three PHM objectives. Table 18 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 8a and 8b.

Table 18: Confirmation of Hypotheses 8a and 8b and the Direction of Coefficients (Organizational Factor: Stage of Implementation of MU of EHRs)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.000	Yes
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Positive	0.000	Yes
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Positive	0.000	Yes
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Negative	0.000	No
	Moderate	Positive	Positive	0.000	Yes
	Comprehensive	Positive	Positive	0.000	Yes

H9a: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to implement the PHM objectives of MU of EHRs, as compared to those that are in states with no laws/policies for public health data reporting.

H9b: All else being equal, the acute care hospitals that are in states with favorable regulatory environments, i.e., having laws/policies for public health data reporting are more likely to have higher level of MU of EHRs for PHM, as compared to those that are in states with no laws/policies for public health data reporting.

Hypotheses 9a and 9b proposed that the presence of public health surveillance state laws/policies in the state of the hospital would be positively associated with the MU of EHRs for PHM. Thus, hospitals which are located in states with favorable laws/policies are expected to be more likely to implement the three PHM objectives of MU of EHRs. Hospitals which are located in states with laws/policies are also expected to be more likely to implement higher level of MU of EHRs for PHM. Hence, hospitals which are located in states with laws/policies are expected to have comprehensive, moderate, minimum level of MU of EHRs for PHM. Hence the expected sign of coefficient for these dependent variables is positive.

The findings of this study show no significant associations between state laws/policies for public health data reporting and any of the dependent variables. The state laws/policies was positively but only marginally significantly associated with the use of EHRs for submission of electronic data to immunization registries and minimum and moderate level of MU of EHRs for PHM. The state laws/policies vary from state to state. Additionally, all the state policies may not be oriented towards enforcing the implementation of MU of EHRs for PHM by acute care hospitals. State laws/policies may encourage the health information exchange through grants for public health agencies to receive the submission of data. The existence of state laws/policies may not influence the hospitals' strategic behavior due to the lack of incentives or due to the lack of mandatory reporting. Table 19 summarizes the results of the hypothesis testing and the direction of coefficients for hypotheses 9a and 9b.

Table 19: Confirmation of Hypotheses 9a and 9b and the Direction of Coefficients (Environmental Factor: State Laws/Policies)

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	p-value	Supported at p<0.05
Model 1: Submission of electronic data to immunization registries	-	Positive	Positive	0.099	No
Model 2: Submission of electronic data on reportable laboratory results to public health agencies	-	Positive	Negative	0.705	No
Model 3: Submission of electronic syndromic surveillance data to public health agencies	-	Positive	Positive	0.475	No
Model 4: Level of MU of EHRs for PHM	Minimum	Positive	Positive	0.078	No
	Moderate	Positive	Positive	0.067	No
	Comprehensive	Positive	Positive	0.163	No

Implications for Theory-Based Research

This study adds to the growing body of existing literature using organizational theory to explain the strategic behavior of health care organizations. This is the only study of its kind to use an organizational theory such as resource dependency theory to explain the MU of EHRs for PHM. This study provides empirical support for resource dependency theory in explaining the organizational and environmental correlates of innovation implementation.

The size of the hospital which represents munificence and system membership and the stage of MU implementation which represent interdependence were significantly associated with the MU objective of submission of electronic data to immunization registries. The size of the hospital which represents munificence and the stage of MU implementation which represents interdependence were significantly associated with the MU objective of submission of electronic data on reportable laboratory results to public health agencies. The size of the hospital which represents munificence, market competition which represents uncertainty, and for-profit status and stage of MU implementation which represent interdependence were significantly associated with the MU objective of submission of electronic syndromic surveillance data to public health agencies. The size of the hospital which represents munificence and the stage of MU implementation which represents interdependence were significantly associated with the level of MU of EHRs for PHM.

Implications for Methodology

This study also makes a significant contribution to the literature by improving the methodology used in previous studies that examined the adoption or implementation of EHRs by U.S. acute care hospitals. Most of the studies have used cross-sectional analyses but have not accounted for the multi-level nature of the data (hospitals nested in states). This study used mixed-effects model which accounted for the hierarchical nature of the data in modelling.

Implications for Policy and Practice

The findings of this study are important from the policy perspective. This study found that the EHRs incentives program and the resulting mandate were positively and significantly associated with implementation of MU of EHRs for PHM. Such incentives programs could be expanded to provide more assistance to the hospitals that have not yet achieved MU. Further, this study found that state laws/policies have no association with the implementation of MU of EHRs for PHM. State policymakers could expand these laws/policies to mandate more hospitals to implement MU of EHRs for PHM. From the practice perspective, this study helps public health agencies to understand which hospitals are more likely to have MU of EHRs for PHM. Since all three PHM objectives involve sending data to public health agencies, this study can help the public health agencies to identify and encourage the MU of EHRs for PHM in hospitals which are not likely to have MU of EHRs for PHM.

Limitations of the Study

Despite the contributions of this study towards theory-driven research, methodology, practice, and policy, this study has certain limitations. Firstly, this study is restricted to non-CAH, non-federal acute care hospitals in the U.S. and the District of Columbia. This study does not include specialty hospitals, CAHs, hospitals in the U.S. territories and other types of healthcare organizations. Hence, the findings of this study may not be generalizable to all hospitals in the U.S. Secondly, this study is a cross-sectional analysis which can only demonstrate association; it fails to establish causality. However, the lagging of the independent variables strengthens causality by addressing the issue of temporal precedence as a requisite to establish causality. Thirdly, this study may also have an omitted variable bias. Finally, this study only considers the macro perspective, i.e. it only considers how organizations behave to implement MU of EHRs for PHM. This study does not delve into the micro perspective, i.e. how individuals within the organizations behave to implement MU of EHRs for PHM.

Suggestions for Future Research

Future research could expand the premise of this study by exploring the impact of implementation of PHM objectives of MU of EHRs on population health outcome measures such as immunization rates and detection of outbreaks. Future research could also examine the financial savings associated with early detection of disease outbreaks using the data collected through PHM reporting of EHR data.

Conclusion

The results of this study provide support for the EHRs incentives program to promote the MU of EHRs for PHM. This study also found the organizational factors of ownership control, size of the hospital, system membership, and teaching status and the environmental factors of market competition to be significantly associated with the MU of EHRs for PHM. These results provide empirical support for using resource dependency theory in examining the organizational strategic behavior of implementation of innovation.

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APPENDIX

State	Description of State law/policy
Alaska	Alaska's public health measure reporting for immunization registry reporting, syndromic surveillance and reportable laboratory reporting is being conducted by utilizing Alaska's HIE. Alaska is requiring all providers submit the Public Health measure data via Alaska's HIE which is then transmitted to Alaska's Department of Health & Social Services, Division of Public Health via a VPN connection between the State and the HIE.
California	The ARRA-funded Immunization (IZ) Gateway serves as a single point of entry for submitting immunization data and enables providers and hospitals to meet meaningful use requirements.
Colorado	Colorado HIO and Health Department have implemented three pilot implementations to support exchange between health care providers and the public health department. The three pilots are Electronic Lab Reporting, Immunization Reporting, and Newborn Screening Orders & Results Delivery. The HIO and Health Department are also partnering to pilot population health data sharing into the Cancer Registry and for syndromic surveillance data. The State has not yet mandated electronic reporting or public health messaging as a matter of policy, but there is an increasing trend and preference toward that approach in light of MU2 requirements.

Illinois	The ILHIE technical core services implementation includes support for a single interface to the Public Health Node, which will facilitate the electronic reporting of data directly from provider EHRs to the Department. Existing point-to-point interfaces for electronic public health reporting will gradually be phased out in favor of the single interface approach, providing a long-term incentive to adopt EHR and acquire HIE service.
Iowa	The IHIN has built capability for electronic submission of both cancer registry data and state reportable disease lab results. Both of these services utilize standard file layouts. In order to use either of these services there must be a signed Participation Agreement.
Kentucky	Kentucky CHFS is pursuing an enterprise network that would be a backbone for the Public Health Reporting and Surveillance systems, MMIS, APCD, HBE, and HIE. KY has mandated that providers electronically report diseases via KHIE.
Maryland	HIE will facilitate certain legally authorized public health uses, such as reportable labs and immunization reporting to public health agencies.
Michigan	The Michigan Department of Community Health (MDCH), Michigan's public health authority, requires public health reporting for meaningful use to be transported through the Michigan Health

	Information Network Shared Services (MiHIN). MiHIN is the state's designated entity to coordinate health information exchange. Providers must select a MiHIN qualified organization or sub-state health information exchange (HIE) to handle the transmission of public health messages.
Nebraska	LB 591 (2011) includes provisions which will facilitate the electronic exchange of syndromic surveillance and immunization information. The Nebraska Department of Health and Human Services (DHHS) Division of Public Health has worked with NeHII to develop bidirectional exchange with the State's immunization registry (NESIIS). NeHII and the Division of Public Health continue to discuss public health reporting through NeHII to the State's syndromic surveillance and disease surveillance systems. The Division of Public Health also worked with Governor Heineman to include \$500,000 in General Funds for FY 2013-14 and \$500,000 in General Funds for FY 2014-15 for the support of health information exchange in the Governor's budget recommendations. Pending inclusion in the State's final budget, this funding can be used to leverage Medicaid's HITECH 90/10 matching funds from CMS.

New Hampshire	In June 2012, the NH General Court passed Senate Bill 288 now allowing healthcare providers otherwise required or authorized by law to submit data to the Department of Health and Human Services to do so through a health information organization. Public Health may now participate in NHHIO and the value of the network has increased. The state previously could not participate in HIE and there were prohibitions against interstate exchange. This service directly impacts providers' abilities to meet meaningful use requirements for public health reporting while aligning meaningful use incentive payments with NHHIO's customer value proposition and sustainability.
New Jersey	The Department of Health's Syndromic Surveillance system, EpiCenter, is used by for early event detection and monitoring of influenza-like illness during flu season, illnesses and injuries associated with a bioterrorism event, infectious disease symptoms, and emerging outbreaks and issues of public health concern in the community through collection of "pre diagnostic" information. The Department of Health's New Jersey Immunization Information System (NJIIS) provides current recommended immunization schedules for infants, adolescents and adults. It consolidates immunization information from all providers into one record to provide an accurate immunization assessment and eliminates the use

	of manual vaccine administration logs. NJIIS assists state and federal agencies with population assessments in the event of a preventable disease outbreak and helps communities assess their immunization coverage and identify pockets of need. The Department of Health's New Jersey State Cancer Registry is a population-based registry that collects data on all cancer cases diagnosed and/or treated in New Jersey since October 1, 1978. The NJSCR serves the entire state of New Jersey, which is estimated to have a population of 8.6 million people.
Oregon	Syndromic surveillance in Oregon (a project called Oregon ESSENCE - Electronic Surveillance System for the Early Notification of Community-Based Epidemics) provides real-time data for public health and hospitals to monitor what is happening in emergency departments across the state before, during and after a public health emergency. With Oregon ESSENCE, hospital users and public health personnel will have a window into the health consequences of emergencies and planned events. Participating facilities are encouraged to leverage Electronic Health Record systems to automate reporting of health records (often in coordination with Federal Meaningful Use preparations).

Pennsylvania	One service offered by the Pennsylvania eHealth Partnership Authority as part of the Pennsylvania Patient and Provider Network (P3N), is the Public Health Gateway (PHG). This joint effort between the Authority, the Department of Human Services, and the Department of Health creates a single point of connection from the private sector to enable submission of reports to various state maintained registries, to include the Cancer Registry, Syndromic Surveillance Registry, Immunization Registry, and Electronic Lab Reporting Registry, all maintained by the Department of Health. Department of Health will work with the PA eHealth Partnership Authority to define and coordinate the exchange of data to the private sector in order to advance population health goals that are currently being developed within the Commonwealth’s Innovation Plan. Future planned PHG enhancements include enabling bi-directional exchange so the private sector can query for information from the public registries, and expansion to include other agencies, possibly to include the Pennsylvania Health Care Cost Containment Council, the Department of Corrections, and the Department of Veterans' Affairs.
Texas	In 2007, Texas passed SB 204, which requires that electronic medical record systems sold to Texas health care providers who administer immunizations be able to interface with the state immunization registry.

West Virginia	The West Virginia Bureau for Public Health utilizes BioSense 2.0 as the State's syndromic surveillance system. Ongoing submission of syndromic surveillance data to BioSense 2.0 is facilitated through the WVHIN's Health Information Exchange (HIE). Hospitals contribute real-time pre-diagnostic data to the HIE and the HIE delivers the data to BioSense 2.0. The Bureau for Public Health and Centers for Disease Control and Prevention (CDC) analyze the data to detect disease outbreaks and epidemics. This syndromic reporting system assists hospitals and providers in meeting Meaningful Use reporting requirements. Public Health Surveillance activities are conducted by several Offices in the WV Bureau for Public Health. Perhaps the highest profile activities are conducted by the Office of Epidemiology and Prevention Services which collects surveillance data under the State's Reportable Disease Rule (§64-7-12) for Immunization Reporting; Syndromic Surveillance; and Cancer Surveillance which are all components of Meaningful Use. Other public health surveillance conducted by this office includes STD/HIV/Hepatitis as well as Food and Waterborne disease. OEPS cooperates with the Office of Laboratory Services to support Electronic Laboratory Reporting for Meaningful Use. In addition to maintaining all of the State's Vital Statistics the Health Statistics Center conducts Public Health Surveillance by conducting surveys

	such as the Behavioral Risk Factor Surveillance Survey and the Youth Tobacco Survey. The Office of Maternal, Child and Family Health's surveillance systems include monitoring of Childhood Lead, Newborn Hearing Screening, the Pregnancy Risk Assessment Monitoring System, and Birth Score system. The Office of Emergency Medical Services maintains the State's Trauma Registry.

Source: State HIT Policy Levers Compendium (HealthIT.gov, July 26, 2016).

Note: State HIT Policy Levers compendium is publicly available for download from https://www.healthit.gov/policy-researchers-implementers/health-it-legislation-and-regulations/state-hit-policy-levers-compendium.