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Adoption of Medication Management Technologies by U.S. Acute Care Hospitals after the HITECH Act

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ADOPTION OF MEDICATION MANAGEMENT TECHNOLOGIES BY U.S. ACUTE CARE HOSPITALS AFTER THE HITECH ACT

by

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ABSTRACT

Medication errors and adverse drug events (ADEs) are a significant public health concern in the United States as they pose a threat to patient safety. The medication management process is a complicated process in U.S. acute care hospitals, consisting of a series of steps such as ordering, transcribing, dispensing and administration and each step is prone to medication errors. The use of technology is considered to be an important intervention in improving the medication management process and thereby reducing medication errors and ADEs and further improve patient safety. The Health Information Technology for Economic and Clinical Health (HITECH) Act, implemented in the year 2011, is the most important regulation in recent years focused on enhancing the use of IT in the health care system. This study examined the organizational and environmental correlates of the adoption of Medication Management Technologies (MMTs) by U.S. acute care hospitals after the HITECH Act.

The rational adaptation perspective of the resource dependence theory is utilized in this study, using panel data from 2009 to 2013 with a one-year lag for independent variables and mixed-effects regression models for analyses. The study operationalized adoption of MMTs through seven measures: global adoption of MMTs, adoption of closed loop medication management, adoption of meaningful use MMTs and adoption-levels for the four steps of the medication management process: ordering, transcribing, dispensing and administration. Hospitals were more likely to adopt MMTs in the time after the implementation of the HITECH Act (2012, 2013) and were less likely to adopt MMTs before the implementation of the HITECH Act (2009,

2010) as compared to the HITECH Act implementation period (2011). The study further found that the resource dependence construct of munificence, operationalized through organizational size, and the construct of interdependence, operationalized through private payer mix was significantly associated with the adoption of MMTs.

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CHAPTER ONE: INTRODUCTION

Statement of the Problem and Rationale

Medical errors are a significant public health concern in the United States (U.S.) as they pose a significant threat to patient safety (La Pietra, Calligaris, Molendini, Quattrin, & Brusaferro, 2005). Further, medication errors are the most common cause of medical errors (Leape et al., 1991). Around 1.5 million Americans suffer from injuries due to medication-related errors annually in hospitals, nursing homes and physician offices (Institute of Medicine, 2006). This number does not include those injuries arising out of the patients' mix-up of medications at home and other settings and thus represents only a fraction of the total population that could be facing medication errors and injuries associated with medication errors (Kohn, Corrigan, & Donaldson, 1999). An Adverse Drug Event (ADE) could potentially be a consequence of medication error. An ADE is a direct measure of patient harm and is defined as "injuries related to medical interventions related to a drug" (Bates et al., 1995). Further, 28% of the ADEs are found to be associated with medication errors, which may be potentially preventable (Bates et al., 1995). Thus, medication errors are directly related to patient safety. Another growing concern is that medication errors and ADEs are costly. One ADE accounts for $2,000 in additional costs excluding the malpractice costs (Bates et al., 1995). In a large tertiary care hospital, ADEs were responsible for $5.6 million annual health care costs and preventable ADEs were responsible for $2.8 million annual health care costs (Bates et al., 1997). The estimated national burden associated with ADEs is $2 billion (Bates et al., 1999).

In U.S. hospitals, the process of medication management is complicated and occurs through a series of steps, comprising of different hospital personnel working in conjunction to accomplish each step of the process (Agrawal, 2009; Bates et al., 2001). The major steps of the medication management process include ordering, transcribing, dispensing and administration (Agrawal, 2009). Ordering involves ordering of the drug by the health care practitioner,

transcribing involves transfer of the prescription information into a medication administration record for the patient, dispensing involves the pharmacist checking the order and providing the drug as per the medication order and administration involves giving the drug to the patient. There is a possibility for errors to occur at each step of this process (Bates et al., 1995; Leape et al., 1995) and hence, the need for interventions to prevent errors at each step of the process, in order to ensure patient safety. Given the impact of medication errors on patient safety, it is essential to implement ways of reducing medication errors, so that the five rights of medication administration (right drug, right patient, right dose, right route and right time) are adhered to (Agrawal & Glasser, 2009).

There is evidence that technology has the potential to reduce medication errors through automating the steps of the medication management process and eliminating sources of errors (Bates, 2000; McKibbon et al., 2012). This further reduces the injuries and ADEs that arise out of medication errors. Since these injuries and ADEs lead to patient harm, their reduction would lead to increased patient safety (Institute of Medicine, 2001). Hence, the use of technology has been touted as an essential tool to improve patient safety (Furukawa, Raghu, Spaulding, & Vinze, 2008). Several organizations in the U.S. such as Leapfrog, the Institute of Medicine (IOM), the Agency for Healthcare Research and Quality (AHRQ) and the Office of the National Coordinator for Health Information Technology (ONCHIT) have recommended the use of technology for improving the medication management process and thereby impacting overall patient safety (McKibbon et al., 2012). The IOM report titled, *'Crossing the Quality Chasm: A New Health System for the Twenty-first Century'* (2001) stresses the need for development of information technology (IT) and its application in improving patient safety (Institute of Medicine, 2001).

Each step of the medication management process can be automated through the use of technology (Bates, 2000). Technologies such as computerized physician order entry (CPOE) and clinical decision support system (CDSS) are used at the ordering step; electronic medication

administration record (eMAR) and in-house transcription software are used at the transcribing step; bar-coding, radio frequency identification (RFID), robot-filling for prescriptions, automated dispensing machines (ADMs) and pharmacy management system are used at the dispensing step; and bar-coding, RFID, eMAR and smart pumps are used at the administration step (Bates, 2000; Bates et al., 2001). For the purpose of this dissertation, these technologies will be collectively referred to as medication management technologies (MMTs). Further, a technology that automates and coordinates all the steps of the medication management process is the closed loop medication management (CLMM) system. This CLMM system is "end-to-end electronic medication management with a seamless flow of information along the process" (Agrawal, 2009). HIMSS identifies the components of the CLMM system as the technologies which automate medication ordering, provide decision support, aid with medication packaging, automate medication dispensing in the hospital units and help with medication administration to provide the correct medication to the right patient (Healthcare Information and Management Systems Society, 2010).

The most important regulation around enhancing the use of IT in the health care system enacted recently has been the Health Information Technology for Economic and Clinical Health (HITECH) Act, which was passed on February 17, 2009 as part of the American Recovery and Reinvestment Act under President Barack Obama's administration (Blumenthal, 2009). Under the HITECH Act, the Office of the National Coordinator for Health Information Technology (ONCHIT) within the Department of Health and Human Services (DHHS), was designated as the main federal organization to promote the adoption of health IT and electronic health information exchange (Blumenthal, 2009). Additionally, the CMS was allocated around $30 billion incentivize providers and hospitals for demonstrating meaningful use of Electronic Health Records (EHRs) through the Medicare and Medicaid EHR Incentive Programs (Centers for Medicare and Medicaid Services, 2014d). The EHR Incentive Programs were designed to

promote the adoption, implementation and upgradation of certified EHR technology and its various functionalities as well as demonstration of meaningful use of that certified EHR technology by eligible providers and eligible hospitals through three stages (Centers for Medicare and Medicaid Services, 2016d). The first stage of this Act came into effect in 2011 with eligible hospitals and providers that meet the objectives set forth in Stage 1 becoming entitled for financial incentives (Centers for Medicare and Medicaid Services, 2016d). The EHR Incentive Programs offered incentives to eligible hospitals and providers who met certain defined objectives known as the meaningful use (MU) objectives (Centers for Medicare and Medicaid Services, 2016d). These objectives and the attached incentives were rolled out in stages, with each stage involving defined measures that needed to be met (Centers for Medicare and Medicaid Services, 2016d). Certain objectives were specific to adoption and use of MMTs in order to gain incentives. These MMTs that were included in the MU objectives at various stages were CPOE, CDSS and eMAR (Centers for Medicare and Medicaid Services, 2014b).

Research on the adoption of MMTs is of interest given the benefits of technology in reducing medication errors and thereby improving patient safety (McKibbon et al., 2012). Further, the enactment of the HITECH Act and the implementation of the stage 1 of the Act created an uncertain regulatory environment for hospitals. Policymakers and legislators would also be interested in the response of the hospitals to the implementation of the HITECH Act, as they would like to know whether the Act enhanced the adoption of technology for medication management in the hospitals. Also, examining the contextual factors of adoption of MMTs at each step of the medication management process is essential to understand the factors associated with this strategic behavior of the hospitals. Previous studies have examined the adoption of selected MMTs individually, but there is a no empirical study that has examined the adoption of the technologies in context of their use in the medication management process. This study is expected to contribute towards the theoretical and empirical literature on organizational responses

of acute care hospitals to the HITECH Act and the strategic behavior of the automation of the medication management process.

Purpose of the Study

The objectives of this study were to:

a. Examine the impact of the implementation of the HITECH Act on the adoption of MMTs by U.S. acute care hospitals.
b. Examine the organizational and environmental correlates of adoption of MMTs by U.S. acute care hospitals.

The variable of adoption of MMTs was measured as: (1) the global adoption of all MMTs, (2) adoption of MU MMTs (CDSS, CPOE and eMAR), (3) adoption of CLMM and (4) the adoption of technologies for each of the four steps of the medication management process i.e., ordering, transcribing, dispensing and administration.

Scope of the Study

This study examined the impact of the implementation of the HITECH Act on the adoption of MMTs as well as the organizational and environmental correlates of the adoption of MMTs by U.S. acute care hospitals. The study examined global adoption of all MMTs, adoption of MU MMTs (CPOE, CDSS and eMAR) and adoption of CLMM and as well as adoption of the technologies used at each step of the medication management process (ordering, transcribing, dispensing and administration of medications).

The scope of this study was limited to the assessment of adoption of MMTs and did not attempt to examine the extent of utilization of these technologies due to the lack of data. Further, this study was also limited to examining the contextual factors of adoption of a strategic behavior and did not attempt to examine the impact of this adoption. The study examined the adoption of MMTs by non-Critical Access Hospitals (CAH), non-federal, acute care hospitals located in the

50 U.S. states and the District of Columbia that had responses recorded in the Healthcare Information and Management Systems Society (HIMSS) Analytics Database. This study was limited to non-CAH, non-federal, acute care hospitals and excluded specialty hospitals such as orthopedic, psychiatric and children's hospitals and excluded federally-owned hospitals such as the Veteran's Affairs Hospitals, Military Hospitals and Public Health Indian Service Hospitals.

Research Questions

This study attempts to answer the following research questions:

1) How did the implementation of the HITECH Act affect the adoption of MMTs in U.S. acute care hospitals?
2) What are the organizational and environmental factors that are associated with the adoption of MMTs in U.S. acute care hospitals?

Overview of the Conceptual Framework

The conceptual framework for examining the research questions of this study was derived from the theoretical framework of resource dependence theory (RDT). RDT is rooted in the premise that organizations and their environment interact with each other and are influenced by each other (Pfeffer & Salancik, 1978). RDT was posited by Pfeffer & Salancik in 1978 and they proposed that organizational survival is dependent on the management of dependencies in the external environment to secure the necessary resources for survival (Pfeffer & Salancik, 1978).

RDT is an open systems theory that is based on the premise that organizations are not self-sufficient and do not have complete control over the resources that are necessary for their survival (Pfeffer & Salancik, 1978). Thus, organizations engage in various strategic behaviors to maintain their dependencies on the external environment and maintain a flow of essential resources (Hatch & Cunliffe, 2013). These resources include financial, human, social or physical resources. These resources are usually scarce and are shared by the organizations in the same market (Pfeffer & Salancik, 1978). Hence, in order to survive in such an environment,

organizations depend on other external entities in the environment. Organizations attempt to acquire resources from their dependent relationships, while still trying to remain autonomous (Pfeffer & Salancik, 1978).

RDT is represented by the three constructs of uncertainty, munificence and interdependence (Pfeffer & Salancik, 1978). Uncertainty refers to the unstable nature of the environment that impacts the availability of resources for the organizations (Pfeffer & Salancik, 1978). In times of uncertainty, organizations make strategic decisions to ensure the flow of resources in the organizations (Hatch & Cunliffe, 2013). The enactment of new regulatory policies that may impact the availability of scarce resources and the competition in the market represents the uncertainty in the environment for the organizations. When new regulatory policies that impact the availability of scarce resources come into effect, organizations may attempt to conform to the policy in order to reduce uncertainty in the environment and maintain a stable flow of resources. In markets with high competition, organizations compete for the same pool of resources (Pfeffer & Salancik, 1978) and survival of the organizations depends on the allocation of these resources. Munificence refers to the abundance of resources in the environment of the organization (Pfeffer & Salancik, 1978). In unfavorable conditions of scarce availability of resources, organizations that are munificent in terms of resources will be more likely to adopt new innovations (Damanpour, 1991). Interdependence refers to the degree of external dependence of the organization (Pfeffer & Salancik, 1978). An organization that is dependent on external entities is likely to have resources through their external dependencies and is also more likely to comply with the demands of these external entities (Pfeffer & Salancik, 1978).

Guided by the RDT framework and the existing literature on the adoption of innovations, the following general hypotheses were proposed in this study:

1) After the implementation of the HITECH Act, U.S. acute care hospitals will be more likely to adopt MMTs.

2) Organizational factors (organizational size, system membership, financial resources, private payer mix and ownership control) and environmental factors (market competition and community wealth in the hospital market) will be associated with the adoption of MMTs by the U.S. acute care hospitals.

Research Hypotheses

The specific research hypotheses that were empirically tested in this study were:

H1: Hospitals will be more likely to adopt MMTs in the period after the implementation of the HITECH Act, all things being equal.

H2: Hospitals located in markets with higher competition will be more likely to adopt MMTs, all things being equal.

H3: Hospitals located in markets with higher community wealth will be more likely to adopt MMTs, all things being equal.

H4: Larger hospitals will be more likely to adopt MMTs, all things being equal.

H5: Hospitals that are part of a multi-hospital system will be more likely to adopt MMTs, all things being equal

H6: Hospitals with greater financial resources will be more likely to adopt MMTs, all things being equal.

H7: Hospitals with a higher proportion of private payer mix will be more likely to adopt MMTs, all things being equal.

H8: For-profit hospitals will be more likely to adopt MMTs as compared to public hospitals, all things being equal.

Significance and Relevance

The implications for patient harm due to medication errors are huge and hence, interventions to prevent these errors are essential. Although, technologies have been known to improve the medication management process by automation of the process and reducing errors, little research has been done to examine the strategic behavior of adoption of technologies specifically for the medication management process. Further, there is a paucity of literature on the impact of the environmental uncertainty of the HITECH Act on the adoption of MMTs by U.S acute care hospitals. Given this background, it is quite relevant from a theoretical and empirical perspective to examine the strategic adoption of MMTs in the context of the changing regulations, especially since the use of MMT can improve patient safety (McKibbon et al., 2012).

Research Plan and Unit of Analysis

This study used panel data of organizational and environmental characteristics and adoption of MMTs. The unit of analysis of this study was the individual non-Critical Access Hospitals (CAH), non-federal, acute care hospital. The research design that was used in this study was the interrupted time series design with no comparison group (Cherulnik, 2001). The study population included all non-CAH, non-federal, acute care hospitals within the 50 U.S. states and District of Columbia that reported data to the HIMSS Analytics Database. The data for this study were obtained from three secondary databases: the HIMSS Analytics Database, the Healthcare Cost Report Information Systems (HCRIS) data and the Area Health Resource File (AHRF). The study sample included all the non-CAH, non-federal, acute care hospitals in the study population that merged across the three data sources, had no missing data for any of the key dependent and independent variables of the study and were observed for all five years of the study period. The measures of the dependent variable were derived from the HIMSS Analytics Database for the years 2009 to 2013, while the independent and control variables were lagged by one year and

were derived from the HIMSS Analytics Database, HCRIS data and AHRF database for the years 2008 to 2012.

This study analyzed the impact of the HITECH Act; organizational factors of size, system membership, financial resources, private payer mix and ownership control; and environmental factors of competition and community wealth on the adoption of MMTs by U.S. acute care hospitals over time. The analytical strategy involved descriptive analyses and regression models to examine the changes in adoption of MMTs. The regressions included fixed effects, random effects and mixed effects models, which are suitable for analyzing panel data.

Outline of Ensuing Chapters

Chapter 2 provides a review of the literature on the steps of the medication management process including the automation of each step of the medication management process through the use of technology; the changes in the regulatory environment of the hospitals in the late 1990s and the beginning of the 21st century, with an emphasis on the HITECH Act; and empirical evidence on the adoption of MMTs by health care organizations in the U.S. Chapter 3 describes the competing perspectives for strategic behaviors of organizations, with a focus on the decision to adopt innovations; elaborates the theoretical framework and develops a conceptual model based on the resource dependence theory and also presents the specific hypotheses that will be tested in the study. Chapter 4 discusses the research methodology including the research design, study population and sample, data sources, key variables and their measurements, analytical strategy, ethical considerations and the methodological limitations of the study. Chapter 5 presents the results of the study. Finally, Chapter 6 provides a discussion of the study results, the implications of the study findings and the limitations of the study and identifies potential areas for future research.

CHAPTER TWO: LITERATURE REVIEW

This chapter summarizes the literature available on the medication management process in U.S. hospitals, as well as the different MMTs used to automate the medication management process. It is comprised of three main sections: (1) The Medication Management Process, (2) Regulatory Environment and (3) Adoption of Medication Management Technologies. The first section describes the medication management process in U.S. hospitals and describes the steps of the medication management process and the technologies that can be used to automate these steps. The second section includes a review of the changing regulatory environment that has had an impact on medication safety and the use of health IT in U.S. acute care hospitals and it also describes the HITECH Act and its objectives in depth. The third section presents the existing empirical literature on the adoption of MMTs in U.S. hospitals.

Section One: The Medication Management Process

Overview of Medication Safety

The IOM has identified six domains of the quality of health care (Institute of Medicine, 2001). These domains are centered on the need for health care to be safe, effective, patient-centered, timely, efficient and equitable (Institute of Medicine, 2001). The AHRQ defines quality of health care as "doing the right thing for the right patient, at the right time, in the right way to achieve the best possible results" (Agency for Healthcare Research and Quality, 2005). Safety of the patient is thus an important aspect of quality in the health care system. Patient safety is defined as,

> "a discipline in the health care sector that applies safety science methods toward the goal of achieving a trustworthy system of health care delivery. It is also an attribute of health care systems; it minimizes the incidence and impact of and maximizes recovery from, adverse events" (Emanuel et al., 2008).

Given the importance of patient safety in health care, medical errors are a significant concern for the U.S. health care system (Kaushal & Bates, 2002). Medical errors are found to be frequent and injuries associated with these errors pose clinical as well as financial ramifications on the health care system (Kaushal & Bates, 2002). One of the first investigations of accidental injuries in hospitalized patients was conducted by the Harvard Medical Practice Study in 1984 in the state of New York. The study found that 3.7% of the hospitalized patients suffered an iatrogenic injury during their hospital stay (Leape et al., 1991). Medication-related events are the most common cause of these injuries, with about 20% of the injuries attributed to medication use (Kaushal & Bates, 2002).

The National Coordinating Council for Medication Error Reporting and Prevention defines medication error as,

> "any preventable event that may cause or lead to inappropriate medication use or patient harm while the medication is in the control of the health care professional, patient, or consumer; where the events may be related to professional practice, health care products, procedures and systems, including ordering; order communication; product labeling, packaging and nomenclature, compounding, dispensing, distribution, administration, education, monitoring and use" (National Coordinating Council for Medication Error Reporting and Prevention, 2015).

Studies conducted by the Adverse Drug Event Prevention Study Group in 1995 defined medication error as, "any error in the process of ordering, dispensing, or administering a drug" (Bates et al., 1995; Leape et al., 1991; Leape et al., 1995). The Agency for Healthcare Research and Quality defines medication error as, "preventable mistakes in ordering and delivering medication to patients" (Agency for Healthcare Research and Quality, 2000).

The World Health Organization (WHO) defines Adverse Drug Reaction (ADR) as, "noxious and unintended and which occurs at doses used in man for prophylaxis, diagnosis or therapy" (World Health Organization, 1972). This definition of ADR, although widely used as an outcome of interest in studying medication-related injuries, assumes that these injuries arise only due to appropriate usage of medications, while the fact is that most of the preventable drug-related injuries arise due to inappropriate use or errors in the use of medications (Bates et al., 1995).

An ADE is a direct measure of patient harm and is defined as "injuries related to medical interventions related to a drug" (Bates et al., 1995). This definition is more comprehensive and is more clinically significant as compared to ADR, since it covers any injury arising out of appropriate or inappropriate medication use (Bates et al., 1995). Potential ADEs are the 'near misses' that could have a considerable probability of harming a patient but did not lead to a harmful event (Kaushal & Bates, 2002). ADEs that are related to a medication error are

considered preventable ADEs, while those that did not result from a medication error are considered non-preventable ADEs (Kaushal & Bates, 2002). Those potential ADEs that were identified and prevented from reaching the patient by a prevention system or intervention are termed as intercepted potential ADEs, while those that reached the patient but did not result in any harm are termed as non-intercepted potential ADEs (Kaushal & Bates, 2002).

The burden of medication errors and ADEs in the U.S. is concerning. Around 1.5 million Americans suffer from injuries due to medication-related errors annually in hospitals, nursing homes and physician offices (Institute of Medicine, 2006). This number does not include those injuries arising out of the patients' mix-up of medications at home and other settings such as ambulatory care and thus represents only a fraction of the total population that could be facing medication errors and injuries associated with medication errors (Kohn et al., 1999). In addition, 28% of the ADEs are found to be associated with medication errors, which may be potentially preventable (Bates et al., 1995). Another growing concern is that medication errors and ADEs are costly. One ADE accounts for $2,000 in additional costs, excluding the malpractice costs (Bates et al., 1995). In a large tertiary care hospital, ADEs were responsible for $5.6 million annual health care costs and preventable ADEs were responsible for $2.8 million annual health care costs (Bates et al., 1997). The estimated national burden associated with ADEs is $2 billion (Bates et al., 1999).

Steps of the Medication Management Process

In U.S. hospitals, medication management occurs through a series of steps, comprising of different hospital personnel working in conjunction to accomplish each step of the process (Agrawal, 2009; Bates, 2000; Leslie, 2010). Thus, medication management is complicated (Agrawal, 2009). The steps of the medication management process include prescribing/ordering, transcribing, dispensing and administration (Agrawal, 2009). The ordering step is a commonly used terminology in a hospital setting, while it may also be referred to as the prescribing step in

outpatient settings (Lisby, Nielsen, & Mainz, 2005). Hence, the term 'ordering step' will be used in this dissertation as it focuses on acute care hospitals. The various steps of the medication management process and the potential for errors at each step is outlined below.

Ordering. The step of ordering involves the clinician, such as a physician, deciding and ordering the course of drug treatment (Leslie, 2010). This includes identifying the name, dose, frequency of intake and route of administration of the drug, intended duration of drug treatment, as well as additional notes essential for safe and efficient drug dispensing and administration (Leslie, 2010). All the components of the ordering steps are prone to error. Ordering errors can arise due to ordering a wrong drug or dosage form or route of administration, the wrong frequency or duration of drug therapy, calculation errors in the dose, overlooking of drug-drug allergies, overlooking or missing to account for the patient's other conditions that could impact the dosage, etc. (Agrawal, 2009; Velo & Minuz, 2009). Most medication errors are reported to happen at this step (Agrawal, 2009). Bates et al. (1995) reported 49% of any potential ADEs to occur as a result of errors at the prescribing/ordering step, out of which 56% ADEs were preventable (Bates et al., 1995).

Transcribing. Transcribing refers to the interpretation and transfer of the prescription drug information, as ordered by the clinician in the ordering process. The information is transferred into a medication administration record for the patient to be further used for drug administration after the drugs are dispensed from the hospital pharmacy (I. C. Wong, Ghaleb, Franklin, & Barber, 2004). However, the rate of adverse events arising due to transcription errors is small. A study by Bates et al. (1995) reported that 11% of the ADEs resulted from errors in the transcribing step, of which 6% of the ADEs could be preventable (Bates et al., 1995).

Dispensing. During the dispensing step, the pharmacist uses the transcribed medication order to provide the drug which matches the dose requirements defined in the order (Leslie, 2010). An error occurs in the dispensing step when there is a discrepancy between the order given

by the clinician and the drug that is actually administered to the patient (Cheung, Bouvy, & De Smet, 2009), or if there is a deviation from the established protocols of the pharmacy (Cina et al., 2006). These errors could arise due to discrepancies such as dispensing of a drug: to a wrong patient, or an incorrect medicine, in the wrong strength, quantity or dosage form, or a medicine that was not compounded correctly, medicine which has incorrect information on the label, or the complete failure to dispense a medication (Cheung et al., 2009). There is a possibility for dispensing errors to go unnoticed owing to the large volume of medications that are dispensed in the hospitals (Agrawal, 2009). Around 11-14% of ADEs arise from errors in the dispensing step and among these, 4% are potentially preventable ADEs (Bates et al., 1995; Leape et al., 1995).

Administration. Medication administration is the step in which the drug that is ordered by the clinician and dispensed by the pharmacist is given to the patient (Leslie, 2010). Errors in the administration step can arise due to discrepancies between the ordered medicine and the administered medicine, which includes: the wrong patient, or drug, dose, dosage form, administration route, time, frequency, treatment duration, or administration of a damaged drug or even the failure to administer the drug (Rodriguez-Gonzalez et al., 2012). Errors in the administration step are the second-most common cause of ADEs, with about 26%-38% of the ADEs occurring due to errors in medication administration, out of which 34% are potentially preventable (Bates et al., 1995; Leape et al., 1995).

Automation of the Medication Management Process

The use of IT has been considered as an essential tool to improve patient safety (Furukawa et al., 2008). Health IT refers to the application of technology towards improvement in the medical treatment and health care of a patient (Fuji & Galt, 2008). Several organizations in the U.S. such as Leapfrog, the IOM, the AHRQ and the ONCHIT have recommended the use of technology for improving the medication management process and thereby impacting overall patient safety (McKibbon et al., 2012). Each step of the medication management process can be

automated through the use of technology (Bates, 2000). Figure 1 was modified from a study published by Bates (2000) to incorporate newer technologies and the major steps of the medication management process (Bates, 2000). This figure outlines the steps of the medication management process as described earlier in this chapter, along with the technologies used to automate these steps and the ensuing discussion focuses on describing these technologies in detail.

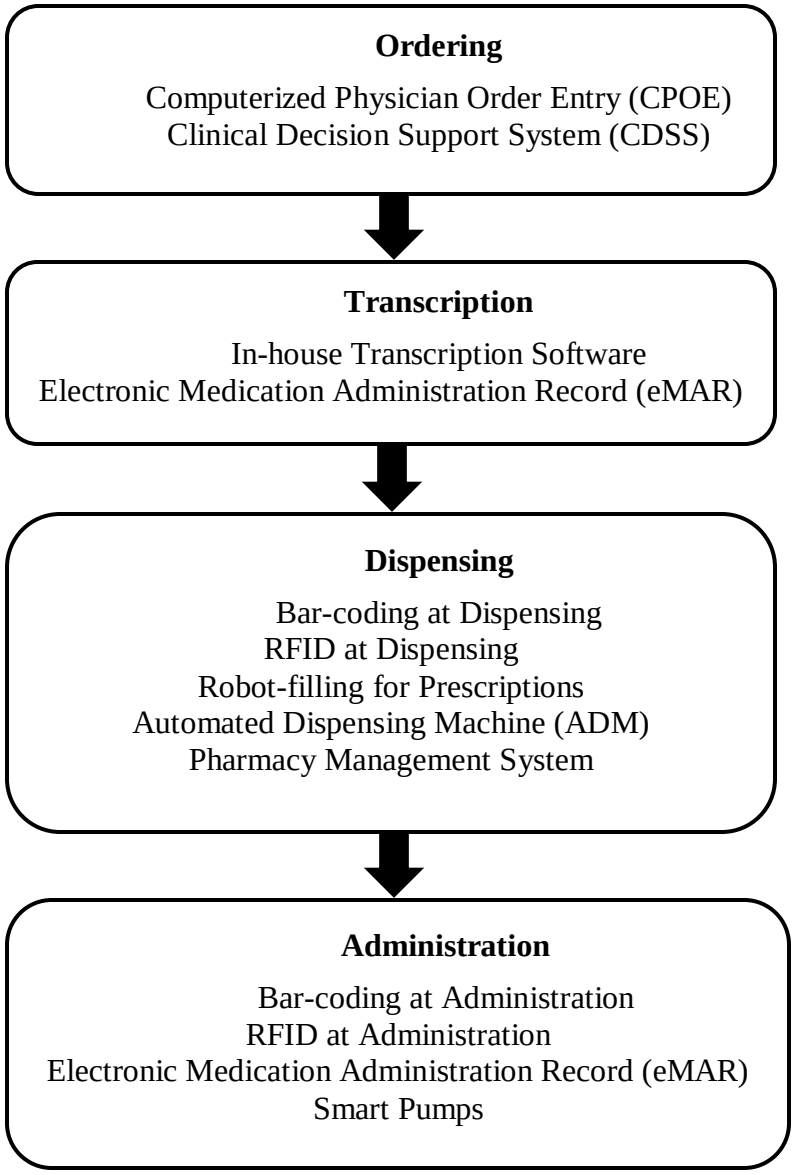

Figure 1: Steps and Automation of the Medication Management Process

1. Electronic Health Record (EHR). Electronic Health Records (EHRs) can incorporate and integrate certain technological tools pertaining to medication management. The Centers for Medicare and Medicaid Services (CMS) defines an EHR as,

> "an electronic version of a patient's medical history, that is maintained by the provider over time and may include all of the key administrative clinical data relevant to that person's care under a particular provider, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports" (Centers for Medicare and Medicaid Services, 2012a).

The Healthcare Information and Management Systems Society (HIMSS) defines an EHR as, "a longitudinal electronic record of patient health information generated by one or more encounters in any care delivery setting". An Electronic Health Record (EHR), which is the electronic version of the patient's medical history, supports several functions that play a role in the medication management process. These functions include the CPOE, ancillary clinical systems for management of results (such as in the laboratory, radiology, pharmacy, etc.), clinical documentation, clinical decision support and bar-coding (Adler-Milstein, Everson, & Lee, 2014). These functions are inter-dependent and there is a need for these functions to work together for the overall improvement in the quality of care (Adler-Milstein et al., 2014). The Meaningful Use (MU) objectives established by the HITECH Act, which have been described in detail in Section Two of this Chapter, established various objectives that require the adoption of these EHR functions. The functions that impact medication management and that are specifically required to be adopted by the MU objectives are: CPOE, CDSS, e-prescribing, drug-drug and drug-allergy interaction checks, maintaining active medication list, maintaining active medication allergy list, implementing drug formulary checks, medication reconciliation and electronic discharge prescriptions (Centers for Medicare and Medicaid Services, 2012b; Centers for Medicare and Medicaid Services, 2014a).

2. Computerized Physician Order Entry (CPOE) and Clinical Decision Support Systems (CDSS). Computerized Physician Order Entry (CPOE) and Clinical Decision Support Systems (CDSS) play an important role in the ordering step of the medication management process (Bates, 2000). Several studies have documented that medication errors and preventable ADEs arising from them are most common at the drug ordering step (Bates, Leape, & Petrycki, 1993; Bates et al., 1995; Kaushal et al., 2001; Leape et al., 1995). Hence, automation of this step is a significant intervention in improving patient safety, as it replaces the paper written orders with electronic ordering (Bubalo et al., 2014; Kaushal & Bates, 2002). CPOE is beneficial in the ordering step in several effective ways. Computerization of the ordering step through the CPOE systems improves medication safety by inculcating a structure into the order so that the clinician must necessarily include the dose, route and frequency of medication administration. Orders through the CPOE system do not have issues of legibility and can be traced back easily to the clinician for further clarifications if needed (Bates, 2000). A pre-and post-implementation study of CPOE at Brigham and Women's Hospital found a 55% reduction in non-intercepted medication errors (Bates et al., 1998). As established by Bates et al. (1999), even a simple CPOE system without any advanced functionalities led to a 64% reduction in medication errors (Bates et al., 1999). Although there are significant costs associated with implementing a CPOE system in a hospital, averaging about US $8 million and an additional US $ 1.35 million annually for maintaining the system for a 500-bed hospital (Bubalo et al., 2014), the cost-benefit analysis of implementing a CPOE system in a 720-bed, academic, tertiary care medical center found that the system saved $28.5 million over a period of ten years (Kaushal et al., 2006). A meta-analysis of the effectiveness of CPOE in reducing ADEs and medication errors in hospitals reported that CPOE implementation was associated with almost half the risk of preventable ADEs and medication errors (Nuckols et al., 2014).

CPOE system can be enhanced further by coupling it with a CDSS (Bates, 2000; Baysari, Westbrook, Richardson, & Day, 2011; Kaushal & Bates, 2002; Kaushal, Shojania, & Bates, 2003). A CDSS is defined as, "as any electronic or non-electronic system designed to aid directly in clinical decision making, in which characteristics of individual patients are used to generate patient-specific assessments or recommendations that are then presented to clinicians for consideration" (Kawamoto, Houlihan, Balas, & Lobach, 2005). One of the factors that is closely associated with ordering errors is the deficiency of medical knowledge (Baysari et al., 2011). Hence, a CDSS system can help eliminate this factor, as it reduces the clinician's dependence on memory and provides access to all the relevant medication information through a drug database system (Baysari et al., 2011; Bubalo et al., 2014). With a CDSS, the medication order can be checked for drug allergies, drug-drug interactions, rechecking the laboratory results for the patients to check for potential problems with some medications, updating discontinued medications etc. (Bates, 2000). The capability of CPOE in combination with CDSS to decrease medication errors and ADEs has been documented widely (Charles, Cannon, Hall, & Coustasse, 2014). A CPOE system with a decision support tool has shown the highest evidence in terms of reducing medication errors, with about 55% to 83% decrease in reported error rates (Bates, 2000). A study at the University Health Network in the Toronto area found that the incremental cost-effectiveness of implementing an electronic medication order entry and a medication administration system was USD $12,700 per ADE prevented (Wu, Laporte, & Ungar, 2007). Mayo Clinic Hospital in Phoenix, AZ found no significant changes in the rate of medication errors in surgical patients after the implementation of the CPOE system in its inpatient unit even after six months and 12 months post-implementation (Stone, Smith, Shaft, Nelson, & Money, 2009). However, this study found that after implementing the CPOE system, the time between the physician placing an order and the nurse receiving it reduced significantly from 41.2 minutes to 27 seconds per order (Stone et al., 2009). A CDSS was implemented in hospitals that were a part of a Catholic health system in the U.S. called Trinity Health, while additional technology such as

CPOE systems along with an advanced CDSS were implemented in a subset of nine hospitals in the system (Roberts et al., 2010). For these nine hospitals, there was a significant increase in the frequency of alerts of potential ADEs that were sent to the pharmacist for review as compared to the hospitals that had only CDSS, out of which 94% were found to be false-positives by pharmacists (Roberts et al., 2010). Of those alerts that were identified as potentially true positives, there was an increase in in the number of true-positives per 1,000 admissions (Roberts et al., 2010). Chertow et al. (2001) found a 13% decrease in the ordering of inappropriate doses and a 24% reduction in the ordering of an inaccurate frequency of medication of nephrotoxic drugs in patients with renal insufficiency after the implementation of a CPOE and CDSS combination (Chertow et al., 2001). Implementation of a CPOE system with decision support at Brigham and Women's Hospital led to an 83% decrease in the occurrence of medication errors (Bates et al., 1999).

Although there are several advantages associated with the use of CPOE, with or without the CDSS functionality, there are also some disadvantages. The increased number of medication alerts due to the CDSS and CPOE system may introduce alert fatigue among the clinician if the threshold for alerting is set too low (Bubalo et al., 2014). A multi-center study of primary care practices found that physicians overrode 94% of the alerts for drug allergy and 89.4% of the alerts for drug interaction alerts that were of high severity (Weingart et al., 2003). Additionally, the transition from paper-based ordering to CPOE systems could be a learning curve for clinician, leading to an increase in the time spent in ordering (Bubalo et al., 2014). Villamañán et al. (2013) reported that that the errors that still occur despite the implementation of CPOE are mainly due to the CPOE technology itself (Villamañán et al., 2013). These include wrong selection of drugs from the drop-down list in the CPOE system, inflexibility with the CPOE structure that leads to the clinician to overuse the free-text section of the CPOE, which causes a discrepancy in the selected medication through the structured format and the free text comments (Villamañán et al.,

2013). Sometimes, the medications selected from the CPOE system are not stocked in the hospital and the CPOE system fails to provide this information to the clinician (Villamañán et al., 2013).

3. Transcription Software. Transcription software is used in the transcribing step of the medication management process (Bates, 2000). Transcribing refers to the interpretation of the dictations given by physicians into a text format (TechTarget SearchHealthIT, 2016a). Earlier, medical transcriptionists were hired to convert these dictations into text (Access Transcription, 2012). However, with the advent of technology, transcription software is now available that can use voice recognition to convert dictations into texts. This software has a database of medical terminologies and has a specialized speech recognition program to aid this process (TechTarget SearchHealthIT, 2016b). The literature on this software is minimal and studies on the use of this software, as well as its impact have not been conducted.

4. Electronic Medication Administration Record (eMAR). The Electronic Medication Administration Record (eMAR) is a software program which is a part of the CPOE system that includes a record of the medications that are transcribed from the orders before medication administration (Hidle, 2007). Hence, it is useful in both the transcribing step and the administration step of the medication management process. It is an electronic documentation of all the medications that the patient has been prescribed along with the medication information such as the appropriate dose, route, frequency, formulation, infusion rate, etc. (Bubalo et al., 2014). The system also allows nurses to document medication administrations and record the reasons for medications that were not given or changed (Bubalo et al., 2014).

Appari and colleagues examined the association between adoption of eMAR and CPOE and medication process quality (Appari, Carian, Johnson, & Anthony, 2012). Medication process quality was measured through 11 evidence-based process measures of adhering to medication guidelines for conditions such as myocardial infarction (AMI), heart failure (HF), pneumonia (PN) and surgical care infection prevention (SCIP) as defined in the CMS Hospital Compare

Database (Appari et al., 2012).The hospitals that adopted eMAR had 14 to 29% higher odds of adhering to ten of the 11 evidence-based process measures for medication process quality, while those that adopted eMAR in conjunction with the CPOE system had a 13 to 38% higher odds of adhering to ten of the 11 evidence-based process measures for medication process quality (Appari et al., 2012). Thus, the combination of CPOE and eMAR led to higher odds of adherence to medication process quality guidelines. Adherence to the guidelines is indicative of higher medication process quality. Association between improved process quality and patient outcomes is well established and thus, improved medication process quality can thereby improve the outcomes of patients and lead to an improvement in patient safety ((Chassin, Loeb, Schmaltz, & Wachter, 2010).

Despite the provision of a real-time medication record, eMAR systems pose certain limitations. Some systems do not allow documentation of medications too far ahead of time or those that were administered too far into the past but were not entered on the eMAR (Bubalo et al., 2014). Additionally, some eMAR systems also do not allow documenting free texts as notes, which was frequently done with the paper administration records where the nurse documented information critical to the medication that was administered (Bubalo et al., 2014).

5. Robot-filling. Robot-filling is used to automate the dispensing of drugs through the use of robots, which increases the precision in filling medication orders (Bates, 2000). The evidence of the use of robots for preventing medication errors is limited, but one study reported a reduction in the dispensing error rate from 2.9% to 0.6% post-implementation of a robot (Weaver, 1998). After installation of a robotic prescription filling system in an independent pharmacy, there was a significant decrease in the filling time for medication orders (Lin, Huang, Punches, & Chen, 2007).

6. Automated Dispensing Machine (ADM). Automated dispensing machines (ADMs) are used in the dispensing step of the medication management process (Bates, 2000). ADMs have

also been identified in the literature as unit-based cabinets (UBCs), automated dispensing devices (ADDs), automated distribution cabinets or automated dispensing cabinets (ADCs) (Institute for Safe Medication Practices (ISMP), 2008). ADMs are decentralized machines used for dispensing medications, storing medications until administration and tracking medication distribution at the point of care (Uy, Kury, & Fontelo, 2015). ADMs allow reducing the pharmacists' work of dispensing medications by permitting the nurses to dispense the drug at the point of care. The medication ordered for the patient is sent to the central server in the pharmacy for review by the pharmacists. Once it is reviewed and approved, the medication appears in the patient's records for the nurses to administer (Chung, Choi, & Moon, 2003). In emergent cases, the pharmacist review can be bypassed through an override (Harolds & Harolds, 2016). The ADM hardware consists of cabinets and drawers that store medications and allow the nurses to withdraw the medications for the patient and the withdrawal is recorded in the pharmacy system servers. Moreover, the server also generates refill requests when any medication in the cabinet falls below a specified threshold and automatically bills the medications to the patient's billing record (Chung et al., 2003). Some systems also provide alerts if a drug has been administered but failed to record on the medication administration record and another nurse tried to give the dose again (Harolds & Harolds, 2016). Thus, an ADM leads to automation of the dispensing step and eliminates the manual actions to fill and pack medications (Baril, Gascon, & Brouillette, 2014). ADMs are beneficial in safeguarding the use of medications and securing the controlled drugs to certain cabinets which cannot be accessed unless it has been reviewed and approved for the patient (Harolds & Harolds, 2016). ADM drawers can also be pre-set to dispense only one medication at a time, which is a needed security measure for controlled and dangerous drugs (Harolds & Harolds, 2016). ADMs can also be linked with a bar-coded system for medication and patient identification (Bates, 2000) and they can also be linked with the CPOE system so that the ordered medication through CPOE is directly sent to the ADM servers (Chung et al., 2003).

A systematic review by Tsao et al. (2014) found evidence that the use of ADMs was responsible for a decrease in medication errors (Tsao, Lo, Babich, Shah, & Bansback, 2014). A study by Chapuis et al. (2012) examined the impact of an ADM in an intensive care setting with an intervention unit and a control unit in the same department of a hospital and found a decrease in the proportion of total error opportunities in the intervention unit and s significantly reduced proportion of total error opportunities after the implementation of ADM as compared to before implementation in the same unit (Chapuis et al., 2010).

7. Bar-coding. Bar-coding helps in identification and can be used in the dispensing process to identify the right drug for the right patient and can also be used in the administration process to make sure the drug that is dispensed is given to the correct patient. Bar-coded systems ensure the five 'rights' of the medication administration process: right patient, right drug, right dose, right route and right time (Agrawal & Glasser, 2009). Bar-coded systems used at the administration step are referred to as bar-coded medication administration (BCMA) system. During medication administration at the point of care, the nurse can scan the patient's identification bracelet and the bar-code on the unit dose of the medication and can detect any discrepancies so that the appropriate drug is given to the right patient (Agrawal, 2009). The bar-code systems can be linked with various other systems in the hospital such as the EMR, eMAR and CPOE (Bubalo et al., 2014; Chung et al., 2003). When a bar-code scanner linked to an EMR is used to scan a patient's identification, the nurse can identify the appropriateness of the medication for the patient (Bubalo et al., 2014). When the unit dose medications are scanned, the nurse can ensure that there are no discrepancies between the medication that has been dispensed and those that are listed on the patient's administration record through a linkage with the eMAR system (Bowers et al., 2015; Bubalo et al., 2014). Interfacing with the CPOE system can help identify if the scanned medication matches with the physician order as entered into the CPOE

(Chung et al., 2003). The use of a bar-coded system permits tracking of medication use, near-misses, as well as medication errors through the link with the EHR system (Bubalo et al., 2014).

Previous studies have reported several advantages of the bar-coded system. The bar-coded system has been shown to reduce 54-87% of errors in the administration of medications (Agrawal, 2009). There was a 68% reduction in the total error rate after the implementation of a bar-coded medication administration (BCMA) system, integrated into the EMR, in an academic inpatient solid organ transplant unit (Bonkowski et al., 2014). A 56% reduction in the medication error rate was reported after the implementation of a BCMA in a community teaching hospital medical intensive care unit with the reported error reductions arising due to the reduction of wrong administration times (DeYoung, Vanderkooi, & Barletta, 2009). In a 36-bed medical surgical unit, there was a 54% reduction in medication administration errors after the implementation of a BCMA and an eMAR system, as compared to the paper MAR system before the intervention (Paoletti et al., 2007). Post-implementation of a bar-code and eMAR system in 35 adult medical, surgical and intensive care units in a 735-bed tertiary academic medical center, there was a 50.8% reduction in the rate of potential ADEs, although this reduction rate was obtained by excluding those ADEs arising due to errors in the timing of medication administration and a complete elimination of transcription errors (Poon et al., 2010). Although this study also reported a 27.3% reduction in the errors in the timing of medication administration, it did not report any significant changes in the rate of potential ADEs arising due to these timing errors, after the implementation of a bar-code and an eMAR (Poon et al., 2010). The cost of implementing and maintaining a BCMA system along with medication dose repackaging and the electronic management systems in the pharmacy was approximately $40,000 per BCMA-enabled bed over a period of five years in a community hospital (Sakowski & Ketchel, 2013). The BCMA system has demonstrated cost-effectiveness, since the cost of implementing the system and operating it over a five-year period are $2,000 per harmful

medication error, which is much lower than the estimated costs if such errors are not averted ($3,100 to $7,400) (Sakowski & Ketchel, 2013).

Even with the implementation of a bar-coding system either in the dispensing or administering step, there are certain medication errors that cannot be completely eliminated and are mostly related to the logistical problems of technology such as mislabeling of medication with the wrong bar-code leading to administration of the wrong medication or the wrong dosage of the right medication, lack of bar-codes on the drugs, bar-codes that could not be scanned, overrides of warnings, circumventing the safeguards of the system, medication administration to wrong patients especially in emergent situations where the medication was scanned after being administered and temporary downtime of the system (Cochran, Jones, Brockman, Skinner, & Hicks, 2007). Specifically, overridden bar-codes led to a substantial number of potential medication errors (Early, Riha, Martin, Lowdon, & Harvey, 2011). Preventing such logistical errors requires attention to the implementation of the system such as protocols to prevent missing labels, scanning authentication, documentation and database maintenance (Bubalo et al., 2014). Certain other disadvantages include increased workload for the nurses during the medication administration step (Bubalo et al., 2014). A case study in an inpatient unit showed a two-fold increase in the number of steps for medication administration one year post-implementation of the BCMA system (Bargren & Lu, 2009).

8. Radio Frequency Identification (RFID). Radio frequency identification (RFID) is another technology that aids with identification and hence, can be used in both the dispensing and administration step. It refers to wireless technology which uses radio waves for identification through microelectronic tags (Ajami & Rajabzadeh, 2013; Zare Mehrjerdi, 2011). The RFID system consists of an antenna that scans for radio waves, a transceiver for data interpretation, a receiver for transmission and receipt of the radio wave frequencies and a transponder, which is the RFID tag attached to the object (Zare Mehrjerdi, 2011). RFID can be used for retrieving

patient information and to identify patients to their corresponding medicines (Ajami & Rajabzadeh, 2013). RFID holds high potential in the medication administration process as each RFID tag is unique to the specific medication that it is attached to and contains information such as the product identification number, cost, date of manufacture, location and inventory, which can be read through a wireless scanner (Zare Mehrjerdi, 2011). Although the function of both bar-codes and RFID is identification, the RFID has certain advantages over the use of bar-codes (Zare Mehrjerdi, 2011). An RFID tag can hold extensive information about the object it is tagged to, as opposed to the limited information on bar-codes (Zare Mehrjerdi, 2011). Also, RFID tags are durable, can withstand x-rays and heat sterilization and are much faster to scan at the rate of 100-1,000 tags per second as opposed to the manual scanning of bar-codes (Zare Mehrjerdi, 2011).

9. Pharmacy Management System. A Pharmacy Management System is an application that provides automation and coordination between all aspects of the pharmacy department and hence plays an important component of automating and coordinating the medication dispensing process (Healthcare Information and Management Systems Society, 2010). It allows the pharmacist to enter and fill the medication order and it also performs all related functions such as billing the patient, re-supply scheduling, inventory management, etc. (Healthcare Information and Management Systems Society, 2010).

10. Intravenous Smart Pumps. Infusion pump systems are used in the medication administration step to administer medications to the patients intravenously (Rothschild, Keohane, Thompson, & Bates, 2003). These pumps have now become highly sophisticated and have a dose error reduction software for the safety of medication administration and have been given the name ‘smart pumps’ (Blandford et al., 2016). This software comprises of a programmable drug library that alerts the nurse if the infusion rates are set as too high or too low as compared to the preset limits for the specific drug (Blandford et al., 2016; Bubalo et al., 2014; Husch et al., 2005). There are usually two types of limits on these smart pumps- soft limit or hard limit (Blandford et

al., 2016; Bubalo et al., 2014). The soft limit provides an alert to the nurse that the programmed infusion rate is beyond the range of the preset, but allows the nurse to continue through an override if confirmed by the clinician (Blandford et al., 2016). However, the hard limit does not permit the nurse to continue the administration of the intravenous medication if the programmed infusion rate is far off from the specified safe range (Bubalo et al., 2014). These preset limits can be modified as per the specific needs of the hospital or the hospital unit (Bubalo et al., 2014). The safety feature helps in preventing dangerous doses of medications and helps in preventing medication errors and ADEs (Bubalo et al., 2014).

11. Closed Loop Medication Management System (CLMM). The technology that automates and coordinates all the steps of the medication management process comprise the CLMM system (Healthcare Information and Management Systems Society, 2010). This CLMM system is "end-to-end electronic medication management with a seamless flow of information along the process" (Agrawal, 2009). HIMSS identifies the components of the CLMM system as the technologies which automate medication ordering (EHR, CPOE), provide decision support (CDSS), aid with medication packaging (robot-filling), automate medication dispensing in the hospital units (ADMs, intravenous smart pumps, bar-code, RFID) and help with medication administration to provide the correct medication to the right patient (eMAR, bar-code, RFID) (Healthcare Information and Management Systems Society, 2010).

Studies evaluating the implementation of a CLMM system have seen limited attempts in the U.S., however, implementation of a closed-loop system consisting of electronic prescribing with basic decision support, automated dispensing in the hospital ward, bar-code for patient identification and eMARs in a teaching hospital in London found evidence that there was a significant decrease in prescribing/ordering errors, decrease in the failure to check patient identity and decrease in medication administration errors (Franklin, O'Grady, Donyai, Jacklin, & Barber, 2007). Additionally, the study also reported a significant increase in the time required to

order a regular inpatient drug and in the time spent in providing a hospital ward with pharmacy services (Franklin et al., 2007). Although the time spent per drug administration round decreased, nursing time on medication tasks apart from the drug rounds increased significantly (Franklin et al., 2007).

Section Two: The Regulatory Environment

Since the establishment of Medicare in 1965, a retrospective cost-based reimbursement system of the private health insurance sector was adopted by Congress for the payment of hospital services provided to Medicare patients (DHHS Office of Inspector General (Office of Evaluation and Inspections), 2001). Under this payment system, the hospital costs for Medicare increased exponentially from $3 billion to $37 billion annually between 1967 and 1983 since the payment systems incentivized the providers to provide more services (DHHS Office of Inspector General (Office of Evaluation and Inspections), 2001). In order to control the costs, a prospective payment system (PPS) was created in 1982, which was a fixed-cost structure per case for inpatient hospital care (DHHS Office of Inspector General (Office of Evaluation and Inspections), 2001). This shift warranted a changing focus towards the quality of care, effective medical decisions and outcomes and cost-containment (DHHS Office of Inspector General (Office of Evaluation and Inspections), 2001).

Institute of Medicine, 1991

In 1991, the IOM called for the need for a computerized patient record (CPR) to provide health care professionals with better access to patient information and lead to an improvement in the delivery of health care (Dick, Steen, & Detmer, 1997). The IOM recommended that the CPR should be a longitudinal record of events related to the person's health (Dick et al., 1997).

Institute of Medicine, 2000

In 2000, the IOM published a reported titled 'To Err is Human: Building a Safer Health System' (Institute of Medicine, 2000). This report shed light on the extent of medical errors in the U.S. health care system (Institute of Medicine, 2000). Through an extrapolation of the analysis of two studies on adverse events- one examining Colorado and Utah hospitals and the other examining hospitals in New York, the report highlighted that at least 44,000 and as many as 96,000 Americans died in hospitals each year due to medical errors (Institute of Medicine, 2000). These numbers were higher than the deaths due to motor vehicle accidents, breast cancer, or even AIDS (Institute of Medicine, 2000). Additionally, over 7,000 deaths were attributed to medication errors annually, which is higher than the number of fatalities caused by workplace injuries (Institute of Medicine, 2000). These numbers shocked the entire nation and drew widespread attention towards this issue of medical errors among the public, media, politicians, as well as the health care professionals (D. A. Wong et al., 2009). The report also contended that preventable ADEs occurred in about two to seven of every 100 hospital admissions (Institute of Medicine, 2000). These events may lead to increased costs. For example, ADEs that could have been potentially preventable were responsible for a $4,700 increase in hospital costs per admission, accounting to $2.8 million in a year for a 700-bed teaching hospital (Bates et al., 1997). The report stressed the importance of addressing patient safety and recommended comprehensive strategic measures that would be needed to be made in the hospitals, as well as the medical processes to reduce medical errors and the injuries resulting from them (Institute of Medicine, 2000). This report also established that at least 50% of the medical errors should be reduced in the next five years (Institute of Medicine, 2000).

Institute of Medicine, 2001

In 2001, an IOM report titled 'Crossing the Quality Chasm: A New Health System for the 21st Century' reported that the use of IT has the potential to transform the health care system in

the country and recommended the use of automated systems for communication of patient information, ordering medications and computerized reminders (Institute of Medicine, 2001). The report called for a nationwide commitment of stakeholders to eliminate majority of the handwritten clinical information by the end of the decade (Institute of Medicine, 2001). In July 2001, the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) adopted new standards for an integrated, organization-specific patient safety program which emphasized the identification of potential errors and highlighted the steps needed to reduce the occurrence of these errors (Cavanaugh, 2001). The Consolidated Appropriations Act of 2001, which includes the Patient Safety Errors Reduction Act calls for implementing error reduction systems and examining safe practices for health care delivery and it also provides legal protection to the organization in order to encourage reporting and collection of errors (Cavanaugh, 2001). This Act led to the establishment of the National Patient Safety Database of reported medical events by the AHRQ, which could be used for research aimed towards improvement in the quality of health care (Cavanaugh, 2001).

President's Health Information Technology Plan, 2004

In July 2004, President George W. Bush announced the President's Health Information Technology Plan, which intended to promote the use of EHRs in the U.S. health care system in the next ten years (The White House, 2009). This plan called for the adoption of health information standards so that medical information could be saved and shared in an electronic system while still assuring privacy and security, doubling of the funding for Health IT demonstration projects, tapping into the Federal Government as the largest buyers of health care to create incentives for the use of EHRs and the creation of a new sub-Cabinet level position of the National Health Information Technology Coordinator who would report directly to the Secretary of Health and Human Services and guide the ongoing efforts for adoption of health IT (The White House, 2009). This led to the establishment of ONCHIT and the American Health

Information Community (AHIC) by the DHHS (Simborg, 2008), which set the foundation for future efforts for promoting Health IT by President Barack Obama (Sheridan et al., 2012).

Institute of Medicine, 2006

In 2006, another report by the IOM titled 'Preventing Medication Errors: Quality Chasm Series' stressed the unacceptable levels of medication errors in the U.S. health care system and outlined a comprehensive approach targeted at decreasing these medication errors (Institute of Medicine, 2006). The report contended that an ADE that arises due to an error is potentially preventable and at least as many as 1.5 million preventable ADEs occur annually in the U.S. (Institute of Medicine, 2006). Even conservative estimates led to annual costs of $3.5 billion due to ADEs (Institute of Medicine, 2006). This report pointed out that the striking aspect of these harmful events was that most of them were preventable through various strategies to reduce medication errors (Institute of Medicine, 2006). To reduce these medication errors, the IOM recommended a series of steps that needed to be taken (Institute of Medicine, 2006). The first step called out for a more patient-centric approach allowing the patient to take on an active role in their medical care, as opposed to a provider-centric approach (Institute of Medicine, 2006). In this approach, the provider would educate, consult and listen to their patients and make way for open communication (Institute of Medicine, 2006). Due to this approach, patients would understand their medications better and take responsibility in managing and monitoring their medications (Institute of Medicine, 2006). The second step placed emphasis on increasing the use of ITs in the ordering and the dispensing steps of the medication administration process, as well as an effective internal monitoring system to detect ADEs more accurately (Institute of Medicine, 2006). The third step was clear and effective communication of drug information through improvement in nomenclature, as well as labeling and packaging of medications (Institute of Medicine, 2006).

Health Information Technology for Economic and Clinical Health (HITECH) Act, 2009

One of the major legislations passed in the recent years that built upon President George W. Bush's President's Health Information Technology Plan was the HITECH Act, which was passed on February 17, 2009, as part of the American Recovery and Reinvestment Act under President Barack Obama's administration. Under the HITECH Act, the ONCHIT within the DHHS, was designated as the primary federal organization to promote the adoption of health IT and electronic health information exchange. Additionally, the CMS was allocated around $30 billion to incentivize providers and hospitals for demonstrating meaningful use of EHRs through the Medicare and Medicaid EHR Incentive Programs (Centers for Medicare and Medicaid Services, 2014d; DesRoches, Audet, Painter, & Donelan, 2013). Starting in 2011, the EHR Incentive Programs were designed to promote the adoption, implementation and upgradation of certified EHR technology, as well as demonstration of meaningful use of that certified EHR technology by eligible providers and eligible hospitals (Centers for Medicare and Medicaid Services, 2016d). The hospitals eligible for the Medicare EHR Incentive Program included those hospitals that are paid under the Inpatient Prospective Payment System, Critical Access Hospitals (CAHs) and Medicare Advantage (MA-Affiliated) hospitals. The hospitals eligible for the Medicaid EHR Incentive Program included those acute care hospitals that had at least 10% Medicaid patient volume and all Children's hospitals (Centers for Medicare and Medicaid Services, 2013).

'Meaningful use' (MU) was measured by a set of core and menu objectives established by the CMS and achievement of these objectives was expected to occur in three stages (Appari, Eric Johnson, & Anthony, 2013). The objectives and requirements were modified and updated through the years of implementation beginning in 2011 (Centers for Medicare and Medicaid Services, 2016d). Stage 1 of MU laid the foundation by establishing standards for electronic data collection of clinical information (Centers for Medicare and Medicaid Services, 2016a). The

Stage 1 objectives (2010 definition) for hospitals to be eligible for the EHR Incentive Programs involved meeting 14 core objectives and five selected menu objectives from a list of ten (Centers for Medicare and Medicaid Services, 2010). The requirements of Stage 1 MU (2013 definition) for hospitals to be eligible for an incentive payment was to meet 13 required core objectives and five selected menu objectives from a list of ten (Centers for Medicare and Medicaid Services, 2014a). The requirements of Stage 1 MU (2014 definition) for hospitals to be eligible for an incentive payment was to meet 11 required core objectives and five selected menu objectives from a list of ten (Centers for Medicare and Medicaid Services, 2014b).

Stage 2 expanded the Stage 1 criteria by requiring the use of health IT for continuous improvement in quality at the point of care and for structured data exchanges. The requirements of Stage 2 MU for hospitals to be eligible for an incentive payment were established in 2014 and the requirements were to meet 16 core objectives and three selected menu objectives from a list of six (Centers for Medicare and Medicaid Services, 2014d). Modified Stage 2 requirements were released by CMS in October 2015 which further specifies the criteria for eligible hospitals to participate in the EHR Incentive Programs in 2015 through 2017 (Centers for Medicare and Medicaid Services, 2016a). Modified Stage 2 criteria established a single set of objectives and measures, by eliminating the menu and core structures, leading to nine objectives for all eligible hospitals (Centers for Medicare and Medicaid Services, 2016b). Setting the objectives for Stage 3 is still underway (Centers for Medicare and Medicaid Services, 2016a). Eligible hospitals received incentive payments from the Medicare Program from fiscal year (FY) 2011 to FY 2015, with decreasing incentives for those hospitals that started receiving payments in 2014 and penalties for those who did not demonstrate meaningful use of EHRs (Centers for Medicare and Medicaid Services, 2016d). Eligible hospitals received incentive payments from the Medicaid Program from FY 2011 to FY 2016, but there were no subsequent penalties (Centers for Medicare and Medicaid Services, 2016d). Hospitals can receive payments from both the Medicare and

Medicaid EHR Incentive Programs if they are eligible (Centers for Medicare and Medicaid Services, 2013).

Patient Protection and Affordable Care Act, 2010

On March 23rd 2010, President Obama signed the Patient Protection and Affordable Care Act (ACA) into law (U.S. Congress, 2010). The ACA was intended to improve the quality and affordability of health insurance through mandates, subsidies and insurance exchanges (U.S. Congress, 2010). One of the important aspects of the ACA was the establishment of accountable care organizations (ACOs) that required physicians, hospitals and other health care providers to provide coordinated care to Medicare beneficiaries and made them jointly responsible for the quality and the cost of care provided (U.S. Congress, 2010). Thus, Health IT has an important place in this initiative of improving health care quality in the U.S., even though the ACA did not specifically impact health IT adoption (U.S. Congress, 2010).

National Action Plan for Adverse Drug Event Prevention, 2013

In 2013, the U.S. DHHS released the National Action Plan for Adverse Drug Event Prevention with the intent to "identify common, preventable and measurable ADEs that may result in significant patient harm and align the efforts of federal health agencies to reduce patient harms from these specific ADEs nationally" (US Department of Health and Human Services, Office of Disease Prevention and Health Promotion, 2014). The ADE action plan identified three initial targets of anticoagulants, diabetes agents and opioids and suggested an approach of surveilling data sources to assess the burden and rates of ADEs, sharing evidence-based prevention tools to prevent ADEs, exploring financial incentives to promote ADE prevention and identifying the gaps in knowledge and future research opportunities for ADE prevention (US Department of Health and Human Services, Office of Disease Prevention and Health Promotion, 2014). This plan intended to promote the implementation of evidence-based guidelines by federal, state and local leaders. The ADE action plan identifies health IT as a helpful tool in supporting its

goals of surveillance, prevention, incentives and research (US Department of Health and Human Services, Office of Disease Prevention and Health Promotion, 2014).

National Patient Safety Goals, 2016

The Joint Commission on Accreditation of Healthcare Organizations (JCAHO) revised its accreditation standards effective from January 1, 2016, through the 2016 National Patient Safety Goals (NPSGs) (The Joint Commission, 2015). The new standards established a few standards specific to medication management such as correct identification of patients through the use of at least two identifiers and safe use of medications through labeling (The Joint Commission, 2015). Thus, medication management has been a priority of several changing regulations over the decade, with the HITECH Act and its MU objectives specifically focused on the use of IT to improve the medication management process.

Section Three: Adoption of Medication Management Technology

The adoption of health IT in health care settings is a complex process. It requires the initial capital to invest into purchasing the technology, transition of the current system and processes into the new technology in different units of the hospital and requires an investment in training the hospital personnel to use the technology in the appropriate manner. Thus, adoption of health IT is not just completed in a short period, it requires a substantial investment of time to achieve the optimal benefits. Further, the benefits of health IT can reach a maximum potential only through the interoperability between different health IT systems, which brings in additional complexity. There is limited research on the adoption of MMTs that automate all the steps of the medication management process. Most studies have focused on the adoption of one specific type of technology, or on the adoption of few similar technologies that may be interfaced with each other.

Adoption of EHRs

The adoption of EHR and its functionalities to achieve the MU objectives and thereby receive incentives has been extensively studied, owing to the focus on the topic after the enactment of the HITECH Act in 2009 and implementation of the MU Stages since 2011. Early studies showed limited adoption of EHRs by hospitals (Jha et al., 2009; Jha, DesRoches, Kralovec, & Joshi, 2010). Data from the American Hospital Association (AHA) IT supplement survey was used widely to assess the adoption of EHRs (Jha et al., 2009; Jha et al., 2010; Jha et al., 2011). The AHA IT supplement survey defined two levels of adoption- comprehensive EHR system as having 24 EHR functions present in all units and a basic EHR system as having ten functions in at least one unit (Jha et al., 2009).

Jha et al. (2009) reported that in 2008, only 1.5% of the U.S. hospitals had a comprehensive EHR system, while 7.6% had a basic system (Jha et al., 2009). These numbers changed modestly in 2009, with 2.5% of the U.S. hospitals having a comprehensive system and 9.2% having a basic system (Jha et al., 2010). Blavin et al. (2010) identified four factors of adoption categories among the 24 functions- electronic clinical documentation, results viewing, CPOE and CDSS (Blavin, Buntin, & Friedman, 2010). Adler et al. (2014) examined if there is a sequence in which a hospital adopts various EHR functions and concluded that hospital characteristics have an impact in the adoption sequence of EHR functionalities. Furthermore, the functionalities of EHR that are usually adopted later in the sequence are CPOE and CDSS, which are integral to MU Stage 1 objectives (Adler-Milstein et al., 2014).

Kazley et al. (2007) examined the organizational and environmental characteristics associated with the adoption of EMRs. This study found that small hospitals, hospitals in an uncertain environment as well as those located in rural areas were less likely to adopt EMRs (Kazley & Ozcan, 2007). The authors of this study contend that the significant characteristics associated with EMR adoption in hospitals represented the barriers that certain hospitals may face

when adopting EMRs (Kazley & Ozcan, 2007). Elnahal et al. (2011) examined the adoption of specific EHR functionalities such as clinical documentation, results viewing, CPOE and CDSS and the impact of hospital quality, based on summary scores for hospital performance in caring for patient with acute myocardial infarction, congestive heart failure, pneumonia and prevention of surgical complications on this adoption (Elnahal, Joynt, Bristol, & Jha, 2011). The study found that hospitals with higher quality are more likely to adopt all EHR functions and most of the low-quality hospitals without EHR functionalities reported no future plans of implementing them (Elnahal et al., 2011).

Achievement of MU

With the enactment of the HITECH Act, there also has been increased focus on research related to the achievement of MU objectives. In 2010, the MU criteria for Stage 1 were much clearer (DesRoches et al., 2010). Among the eligible hospitals, 4.4% met the definition for MU Stage 1 in 2010 (Jha et al., 2011), while 18.4% satisfied the definition in 2011 (DesRoches, Worzala, Joshi, Kralovec, & Jha, 2012). Since then, these numbers have been increasing steadily as the MU Stages rolled out and payments were made by the EHR incentive program. In 2012, 38% of the eligible U.S. hospitals received Medicare MU incentive payments (Diana, Harle, Huerta, Ford, & Menachemi, 2014). Diana et al. (2012) attempted to examine the intent of the hospitals to apply for the MU incentives (Diana, Kazley, Ford, & Menachemi, 2012). Intent to apply for the MU incentives was examined through the 2009 AHA Annual Survey Information Technology Supplement, in which hospitals were asked if they are pursuing the incentive program and examined the reasons for not pursing them (Diana et al., 2012). The study found that more than half of the U.S. hospitals intended to apply for MU incentives in 2011, while almost one-fourth reported their intent to pursue the incentives in 2012 (Diana et al., 2012). The study also found that despite the monetary incentives in achieving MU of certified EHRs, certain hospitals such as those that already have a partial EHR system or a complete EHR system, larger

hospitals and urban hospitals were more likely to plan to seek incentives, while for-profit hospitals and system members were less likely to do so (Diana et al., 2012). This finding that those hospitals without an EHR were less likely to apply for MU objectives raised a question of whether the HITECH Act was just impacting the EHR users to achieve MU, instead of impacting the non-adopters of EHRs to adopt them and then achieve MU (Diana et al., 2012). Similarly, EHR adopters continued to be more likely to receive the MU incentives, as compared to non-adopters (Diana et al., 2014). The authors thus contend that the EHR incentive payments may have provided a disproportionate advantage to the hospitals that had already adopted an EHR system prior to the start of the incentive program and hence may not be effective in the goal of widespread EHR adoption and its meaningful use (Diana et al., 2014). Further, about 30% of the hospitals that had the infrastructure in place to achieve the MU objectives failed to report their eligibility to receive the MU incentives (Diana et al., 2014). The reason for this has been attributed to the inability to meet the MU objective measure for CPOE (Diana et al., 2014).

Adoption of MMTs

Zhang et al. (2013) examined the differences between the U.S. acute care hospitals that adopted health IT and those that did not (Zhang et al., 2013). They examined 52 technologies by clustering them into clinical IT, administrative IT and strategic decision making IT and found that the most important factors that are significantly associated with the adoption of IT are large size, urban location of the hospital and HMO penetration (Zhang et al., 2013). This study was conducted using data from the year 2006 i.e., before the enactment of the HITECH Act. Thus, the study recommended examining the impact of the EHR Incentive program in 2011 on the adoption of IT by U.S. acute care hospitals (Zhang et al., 2013).

Uy et al. (2015) examined the trends in the adoption of bar-code, RFID, biometric and pharmacy automation technologies in US hospitals using the HIMSS Analytics Database (Uy et al., 2015). The study found that the medication administration department had the highest growth

rate for bar-code and RFID technologies (Uy et al., 2015). Further in 2012, bar-coding had a high adoption rate (73.9%) in the pharmacy department (Uy et al., 2015). High adoption rates were also observed for the pharmacy automation technologies such as ADM (81%), with steady growths in the adoption of carousels and robot-filling for prescriptions (Uy et al., 2015).

A study by Furukawa et al. (2008) examined the adoption of eight MMTs and is one of the few studies that attempts to examine technologies specifically used for automation of the medication management process (EMR, CDSS, CPOE, bar-coding at medication dispensing, robot for medication dispensing, ADM, eMAR and bar-coding at medication administration) and the factors associated with their adoption (Furukawa et al., 2008). This cross-sectional study used the HIMSS Analytics Database and limited the sample to acute care hospitals in the U.S. (Furukawa et al., 2008). The measure of health IT adoption was a binary variable of adoption of technology (1 if adopted, 0 otherwise) and a count variable for the number of health IT applications that were adopted (Furukawa et al., 2008). The results revealed the highest adoption rate for ADMs at 62%, followed by CDSS (46%), EMR (37%), bar-coding at medication dispensing (27.1%), eMAR (26%), CPOE (14%), robot (7%) and bar-coding at medication administration (5%) (Furukawa et al., 2008). The study also found that hospitals with certain characteristics had a higher likelihood of adoption of health IT such as larger hospitals, teaching hospitals and hospitals with system membership and JCAHO accreditation (Furukawa et al., 2008). Also, rural hospitals, investor-owned and state/local government hospitals and hospitals with a higher share of Medicare discharges and higher share of Medicaid discharges were less likely to adopt health IT systems, although the probability of adoption varied by the type of technology (Furukawa et al., 2008). The study also established evidence for an important aspect that could influence health IT adoption, which were the safety initiatives in the state such as patient safety coalitions, adverse-event reporting systems and patient safety centers (Furukawa et al., 2008).

Cutler et al. (2005) examined the reasons for low adoption of CPOE from the point of view of financial and ownership status theories. They found that government hospitals and teaching hospitals are more likely to invest into the implementation of CPOE at that time (Cutler, Feldman, & Horwitz, 2005). Appari et al. (2012) examined the adoption of two technologies for medication safety- CPOE and eMAR and found that adoption of eMAR alone as well as in combination with CPOE improved adherence to medication guidelines in the hospitals (Appari et al., 2012).

Summary of Gaps in the Literature

The current empirical literature has examined the factors associated with EHRs and achievement of MU objectives widely. A few studies have also focused on the adoption of different MMTs. However, there is a paucity of empirical organizational studies that examines MMTs in context of their functions in the steps of the medication management process. Additionally, there has not been a study that examines the factors associated with adoption of CLMM. Further, the impact of the implementation of the HITECH Act on adoption of MMTs is still unknown. Since adoption of MMT is the first step towards their implementation leading to reduction in medication errors and improvement of patient safety, there is a need to examine the changes in the adoption of MMTs after the implementation of the HITECH Act.

Summary of the Chapter

This chapter presented an overview of medication safety in U.S. hospitals with a discussion of the steps of the medication management process and the technologies that are used to automate the medication management process. The regulatory environment in which the U.S. hospitals function with regards to adoption of health IT with a focus on the HITECH Act and the MU objectives is discussed. Finally, the empirical literature available on the adoption of MMTs by U.S. hospitals is presented. A review of this literature indicated the important implications of the HITECH Act in the adoption of MMTs. It also indicated a dearth of empirical organizational

studies that examine the adoption of MMTs in the context of the different steps of the medication management process.

CHAPTER THREE: THEORETICAL BACKGROUND

This chapter consists of two sections. The first section explores the competing perspectives that have been used in the literature to examine organizational strategic behavior, specifically focusing on the organization's decision to adopt innovations. The second section of this chapter discusses the theoretical framework for this study and the development of the conceptual model, key constructs and research hypotheses that were empirically tested in this study. The theoretical framework presented in this chapter attempts to answer the two research questions of this study as described below:

1) How did the implementation of the HITECH Act affect the adoption of MMTs in U.S. acute care hospitals?
2) What are the organizational and environmental factors that are associated with the adoption of MMTs in U.S. acute care hospitals?

Section One: Competing Perspectives for Organizational Strategic Behavior

Organizational Strategic Behavior

Until the late 1950s, a closed systems perspective was dominant and organizational behavior was considered to be through the actions occurring due to solely the internal operations and events of that organization (Hatch, 1997). However, open systems theorists established that organizations are influenced by their environment and introduced the idea of a relationship between organizations and their environment (Scott & Davis, 2003). Organizational environment was commonly categorized as the inter-organizational network, the general environment and the international/global environment (Hatch, 1997). Each organization interacts with the members in its environment and develops an inter-organizational network (Hatch & Cunliffe, 2013). The general environment refers to the "more general forces" that have an impact throughout the network, while the international/global environment consists of the forces that are not limited to the national boundaries and act on a global-level (Hatch, 1997). Analyzing the general environmental conditions is more useful in examining the relationship between the organization and its environment (Hatch, 1997). Hence, in the late 1950s and early 1960s, the framework of the relationship between organizations and their environment and the importance of this concept was developed and in the period from late 1970s continuing till today, the environment has been considered to have an important influence on the organization (Hatch, 1997). Organization theories during this time were developed to understand the way in which this influence works (Hatch, 1997). In this period, the three most influential theories surrounding the organization-environment relationship were developed and have been widely used since. These theories are the resource dependence theory (RDT), population ecology theory and institutional theory (Hatch, 1997).

RDT establishes that an organization is dependent on its environment for resources and the need for resources such as raw materials, labor, capital, equipment, knowledge and outlets for

its products and services renders the organization vulnerable and provides the environment with control over the organization (Hatch & Cunliffe, 2013). This theory provides a framework to understand the dependencies of the organization on its environment and strategies for managing these dependency relationships (Pfeffer & Salancik, 1978). The dependence between the organization and its environment is a complex one, in the sense that is "neither singular nor undifferentiated" (Hatch & Cunliffe, 2013). Assessing resource criticality as well as scarcity in order to prioritize the management of dependencies is an essential component of the resource dependence perspective (Hatch & Cunliffe, 2013).

Population ecology theory is similar to RDT in the assumption of organizational dependence on the environment for resources, but they differ in their points of view, as the population ecology theory looks at organizations from the perspective of the environment (Hannan & Freeman, 1977). This theory posits that the environment has control over selecting those organizations to survive which best fit the needs of the environment (Hatch, 1997). Population ecologists are interested in understanding the successes and failures of organizations competing for the same pool of resources (Hatch & Cunliffe, 2013). Researchers find that the application of the population ecology theory to organizational management is difficult owing to the unit of analysis being outside the boundary of the organization and thereby outside organizational control (Hatch & Cunliffe, 2013). Additionally, this theory is applicable to highly competitive populations and may not be justifiable in all contexts (Hatch & Cunliffe, 2013).

Both the resource dependence and population ecology theories emphasize the necessity of resources for the organization's survival, while the institutional theory recognizes sociocultural demands that the organization must conform to in order to ensure its survival (Hatch, 1997). These are referred to as institutional pressures and are the norms, values and expectations that lead to the social legitimacy of the organization in the environment, which may be as important for the organization's survival as any other resource (DiMaggio & Powell, 1983). Institutional

theorists believe that in addition to technical, economic and physical demands, environments also place social, cultural, legal, or political demands that require organizations to engage in certain behaviors for the sake of acceptance in the society (Hatch & Cunliffe, 2013).

These three theories provide three unique perspectives, but they are unified by the common idea of the impact of the environment on the organization (Hatch, 1997). These theories emphasize the concept of "strategic fit" of the organization referring to the actions taken by the organization to comply with the demands of the environment and ensure its survival (Hatch, 1997). A strategist is concerned with interpreting these theories into strategies that can help the organization to take actions that provide them with a competitive advantage to ensure their survival (Hatch, 1997). The view point of the RDT aligns with that of the strategist, which is centered on the organization rather than the environment and the framework of the theory can be converted into opportunities to strategize and achieve fit (Hatch, 1997). The strategist interprets institutional theory as managing the aspects of the organizations that would lead to the organization being legitimate and thereby, attract resources from the environment (Hatch, 1997). This could be done by imitating the successful organizations, by conforming rules, regulations or sanctions, or by following behaviors of peer organizations (Scott & Davis, 2003). This imitation could also be a strategy to ensure selection and retention by the environment, through the population ecology perspective (Scott & Davis, 2003).

For the purpose of this study, the adaptive perspective of the RDT was considered to be a better fit than institutional theory. This is because the adoption of MMTs is likely to be not random and is a conscious strategic behavior of the hospital owing to the extent of the resource input that is needed. MMTs are expensive and their use also requires the need to train staff. Hence, for a strategic decision such as adoption of MMTs, hospital leadership needs to account for the availability of resources in order to make this investment. The HITECH Act added a regulatory pressure on the hospitals, however the resources needed to adopt MMTs go much

beyond the incentives offered by the HITECH Act, especially for those hospitals that do not already have the infrastructure of EHR in place (Diana et al., 2014). Hence, the decision to adopt MMTs in context of the HITECH Act is more likely to be based on the availability of resources rather than to gain legitimacy. Thus, this study utilized the adaptive perspective offered by RDT in order to develop the framework to examine the organizational strategic behavior of adoption of MMTs. As described above, RDT assumes that organizations engage in strategies to improve their chances of survival in an uncertain environment. Previous literature supports the adoption of this perspective when examining strategic choices by organizations, as evidence suggests that the leadership of the organization make strategic choices for environmental adaptation (Alexander & Morrisey, 1989; Augier & Teece, 2009; Floyd & Wooldridge, 1997). Further, RDT has been applied widely to study the adoption of technologies by hospitals in the health services research literature (Kazley & Ozcan, 2007; Menachemi, Shin, Ford, & Yu, 2011; Menachemi, Mazurenko, Kazley, Diana, & Ford, 2012).

Organizational Innovation

In a dynamic environment, innovation has been considered as a means of competitive advantage for the organizations. In fact, innovation is considered to be the most valuable aspect of a firm's performance. Crossan & Apaydin (2010) established a comprehensive definition of innovation as:

> "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)."

The core intention of adopting innovations is to enhance the performance of the organization and it can be done either as a reactive strategy to tackle the changes in the environment or as a proactive strategy to bring about a change in the environment (Damanpour,

1991). As organizations adopt innovations continually to keep up with the dynamic nature of the environment, Damanpour (1991) contended that, “organizational innovativeness is more accurately represented when multiple rather than single innovations are considered” (Damanpour, 1991).

Three distinctions in the type of innovations have been made in the literature as service, administrative process and technological process innovations (Damanpour, Walker, & Avellaneda, 2009). Service innovations refer to the introduction of new services or introducing existing services to new clients (Damanpour et al., 2009). Administrative innovations include those innovations that bring forth a change in the structure of an organization (Damanpour et al., 2009). These innovations are those that impact the basic activities in the organization and are directly linked to the management of the organization (Damanpour et al., 2009).Technological innovations are those that lead to changes in technology in the organization (Damanpour et al., 2009). Technology is “a tool, technique, physical equipment or system by which the employees, the units, or the organization extend their capabilities” (Damanpour, 1987). Thus, technological innovations can be considered to be new tools, techniques, device, or system (Damanpour, 1987).

From the perspective of organizations being open systems, it is considered that organizations adopt innovations due to environment pressures and as a means to maintain or improve performance. Organizations are considered as adaptive systems, which introduce change to adapt with the changing environment and to continue to function in that environment (Damanpour et al., 2009). Multiple factors such as individual, organizational and environmental factors are considered to have an impact on the adoption of innovations. Among these, organizational factors have been widely examined and have been considered as primary determinants of organizational innovation (Damanpour, 1991). The external environment provides opportunities and constraints on the organizational adoption of innovation (Damanpour & Schneider, 2006). Further, organizational leaders and managers are constituted to be influential

in innovation adoption as they control the resources and major decisions for the organization (Damanpour & Schneider, 2006).

Adoption of Innovation

Previous studies on the adoption of innovation have majorly focused on the effect of organizational factors on the adoption of innovation, while few have also considered the effect of other contextual factors such as environmental effects and top managerial factors. Kimberly & Evanisco (1981) examined the influence of individual, organizational and contextual factors on the adoption of technological and administrative innovation by hospitals (Kimberly & Evanisko, 1981). In this study, technological innovations were those innovations that were related to the diagnostic and treatment capabilities of the hospital and were directly related to the working of the hospital (Kimberly & Evanisko, 1981). On the other hand, administrative innovations were those that were not directly related to the working of the hospital and included the adoption of electronic data processing for internal logistical activities of the hospital (Kimberly & Evanisko, 1981). The study found that the individual, organizational and contextual factors included in the study were better in terms of predicting adoption of technological innovations rather than administrative innovations (Kimberly & Evanisko, 1981). Also, there were differences in terms of which factors influence the adoption of which type of innovation. The study also established that the organizational level factors were superlative than other factors for predicting adoption of both types of innovations (Kimberly & Evanisko, 1981).

Damanpour (1987) examined organizational factors as predictors of adoption of technological, administrative and ancillary innovations in public libraries and established that the organizational factors were better at predicting adoption of technological innovations, rather than administrative or ancillary innovations (Damanpour, 1987). An important conclusion that was established from this study is that it is essential to distinguish between types of innovation, as

well as the stages of adoption of the innovation when studying innovation adoption (Damanpour, 1987).

Damanpour (1991) conducted a meta-analysis of the effects of organizational determinants on innovation adoption (Damanpour, 1991). This study found that there was a positive association between innovation adoption and specialization, functional differentiation, professionalism, attitude of managers towards change, resources of technical knowledge, administrative intensity, slack resources as well as external and internal communication (Damanpour, 1991). The factors of resources of technical knowledge and slack resources closely aligns with 'munificence', which is a construct of RDT (Pfeffer & Salancik, 1978). The study also established a negative association between adoption of innovation and centralization; and no significant association between adoption of innovation and formalization, tenure of manager and vertical differentiation (Damanpour, 1991).

Damanpour & Gopalakrishnan (1998) examined the role of environmental change in the theories of the relationship between organizational structure and innovation adoption (Damanpour & Gopalakrishnan, 1998). This study established four scenarios in the environment based on the high and low levels of stability and predictability (Damanpour & Gopalakrishnan, 1998). In a stable and predictable environment, it was contended that the speed of innovation adoption is slow and the rate of adoption is low (Damanpour & Gopalakrishnan, 1998). In a stable but unpredictable environment, the rate of adoption is low though the speed is fast (Damanpour & Gopalakrishnan, 1998). In an unstable and predictable environment, the rate of adoption is high, while the speed is moderate (Damanpour & Gopalakrishnan, 1998). And finally, in an unstable unpredictable environment, the rate of adoption is high and the speed is fast (Damanpour & Gopalakrishnan, 1998). Thus, this study established the crucial role that the environmental state plays in the adoption rate and the rate of innovation adoption.

A study conducted by Damanpour & Schneider (2006) on the effect of environment, organizational and top managers' characteristics on the phases of adoption of innovation found that organizational factors as well as the attitudes of the top managers were better predictors of each phase of innovation as compared to environmental factors and the demographic characteristics of the top managers (Damanpour & Schneider, 2006). The study defined the phases of innovation as initiation, adoption decision and implementation of innovation (Damanpour & Schneider, 2006).

These studies on adoption of innovation establish the important role that the organizational and environmental characteristics play in the strategic decision of adoption of innovation. Further, the importance of examining multiple innovations as well as distinguishing between the different types of innovation and the phases of innovation have been brought forth.

Section Two: Theoretical Framework of the Study

The ensuing paragraphs describe the conceptualization process for the two research questions of the study:

1) How did the implementation of the HITECH Act affect the adoption of MMTs in U.S. acute care hospitals?
2) What are the organizational and environmental factors that are associated with the adoption of MMTs in U.S. acute care hospitals?

The RDT perspective was used to derive the framework to answer these research questions.

Overview of Resource Dependence Theory

Resource dependence theory (RDT) was proposed by Pfeffer and Salancik (1978) in their book, *'The External Control of Organizations: A Resource Dependence Perspective'.* RDT posits that organizational survival is derived from its ability to manage environmental demands and acquire resources from the environment that are critical for its survival (Pfeffer & Salancik,

1978). This macro-organizational theory is based on an open systems perspective and provides a rational approach to understand the control that the environment has over the organizations (Pfeffer & Salancik, 2003). The open systems perspective proposes that no organization is fully self-sufficient in terms of the resources necessary for its survival and must engage in exchange relationships with its environment in order to secure these resources (Scott & Davis, 2003).

The RDT provides a framework to understand the dependence of the organization on its environment in order to acquire resources, since all necessary resources cannot be obtained from within the organization itself (Scott & Davis, 2003). Hence, organizations may alter their structure or certain behaviors in order to acquire and maintain its resources (Scott & Davis, 2003). Organizations strategize to gain critical scarce resources in order to deal with uncertainty and scarcity in the environment and reduce their dependency on others (Jaana, Ward, Pare, & Sicotte, 2006; Verbruggen, Christiaens, & Milis, 2011). Thus, many of the observed actions of an organization may reflect the organization's intention to secure resources from the environment (Banaszak-Holl, Zinn, & Mor, 1996). Given the scarcity of resources in the environment, RDT posits that organizational operate rationally in such an environment by maintaining their dependencies on external entities, but not losing complete autonomy (Scott & Davis, 2003).

Thus, the core tenet of RDT is that organizations strategize to acquire critical resources from the environment in order to ensure survival in times of uncertainty, while maintaining interdependent relationships with external organizations. RDT has been widely used in health services research to examine and explain various strategic behavior of health care organizations such as provision of various innovative services (Banaszak-Holl et al., 1996), staffing changes (Nayar, 2008), adoption of technology (Kazley & Ozcan, 2007), alliances (Zinn, Proenca, & Rosko, 1997), strategic responses to improve efficiency (Apenteng, Nayar, Yu, Adams, & Opoku, 2015), quality improvement and management initiatives (Zinn, Weech, & Brannon, 1998) and contractual strategies (Alexander & Morrisey, 1989; Apenteng, Nayar, Yu, Adams, & Opoku, 2015; Kazley & Ozcan, 2007; Nayar, 2008)

The three key constructs specified by RDT include uncertainty, munificence and interdependence (Scott & Davis, 2003). Uncertainty refers to the unstable nature of the environment that plays a role in the availability of resources (Pfeffer & Salancik, 1978). RDT posits that organizations depend on the environment for scarce resources and when faced with uncertainty in the environment, they are more likely to adopt strategic behaviors that could help them secure a stable flow of resources (Pfeffer & Salancik, 1978). This behavior would thereby minimize the uncertainty in the environment and improve the chances of organizational survival (Hatch & Cunliffe, 2013). Uncertainty usually arises due to competition in the market when more organizations must share the same resources, or under regulatory changes. Thus, in highly competitive markets, organizations would be more likely to try to innovate in order to differentiate themselves from other organizations. Additionally, regulatory pressures from government agencies such as policy enactment that affects access to financial resources for an organization creates an uncertainty in the flow of resources for the organization. Thus, in order to maintain the flow of these financial resources into the organization and maintain stability in an uncertain environment, organizations could engage in strategies that facilitate this. If this involves complying with the objectives of the policy, organizations would be more likely to try to align with the regulations of the policy to ensure survival.

Munificence represents availability and accessibility of resources in the environment (Pfeffer & Salancik, 1978). RDT posits that organizations that have access to critical resources will be more likely to have the capacity to adopt innovations (Damanpour et al., 2009). In the health care industry, munificence is represented by abundance of resources in the market, as well as the size of the organization (Alexander & Morrisey, 1989; Apenteng et al., 2015; Kazley & Ozcan, 2007; Nayar, 2008).

Interdependence refers to the degree to which organizations are dependent on other organizations for resources (Pfeffer & Salancik, 1978). Organizations with interdependent relationships are more likely to have availability of resources to adopt innovations (Damanpour,

1991). Further, those organizations that are dependent on external entities for resources are more likely to comply with the demands of these external entities (Pfeffer & Salancik, 1978). In the health care industry, interdependent relationships arise through dependence on external entities, for example Medicare, for resources such as patients or funding (Kazley & Ozcan, 2007; Nayar, 2008), or through dependence on shareholders for for-profit hospitals (Apenteng et al., 2015; Kazley & Ozcan, 2007).

Development of the Conceptual Model

When utilizing the RDT framework to examine the strategic behavior of an organization, the unit of analysis is the organization. In this study, 'organization' is defined as the individual acute care hospital. RDT emphasizes an adaptive perspective by the adoption of strategic behavior to maintain critical or scare resources that are essential to the organization's survival (Scott & Davis, 2003). For an acute care hospital, these critical resources include patients, clinicians, other health care professionals, financial capital, payers and complying with regulations. The adoption of MMTs can be viewed as a strategic behavior to stabilize these resources and minimize the organization's dependencies, while ensuring the survival of the organization in an uncertain environment.

The conceptual model of the study shown in Figure 2 provides an illustration of how the strategic behavior of adoption of MMTs by the focal organization i.e., the individual acute care hospital, is influenced by various environmental and organizational factors. These factors were derived from the key constructs of RDT- uncertainty, munificence and interdependence.

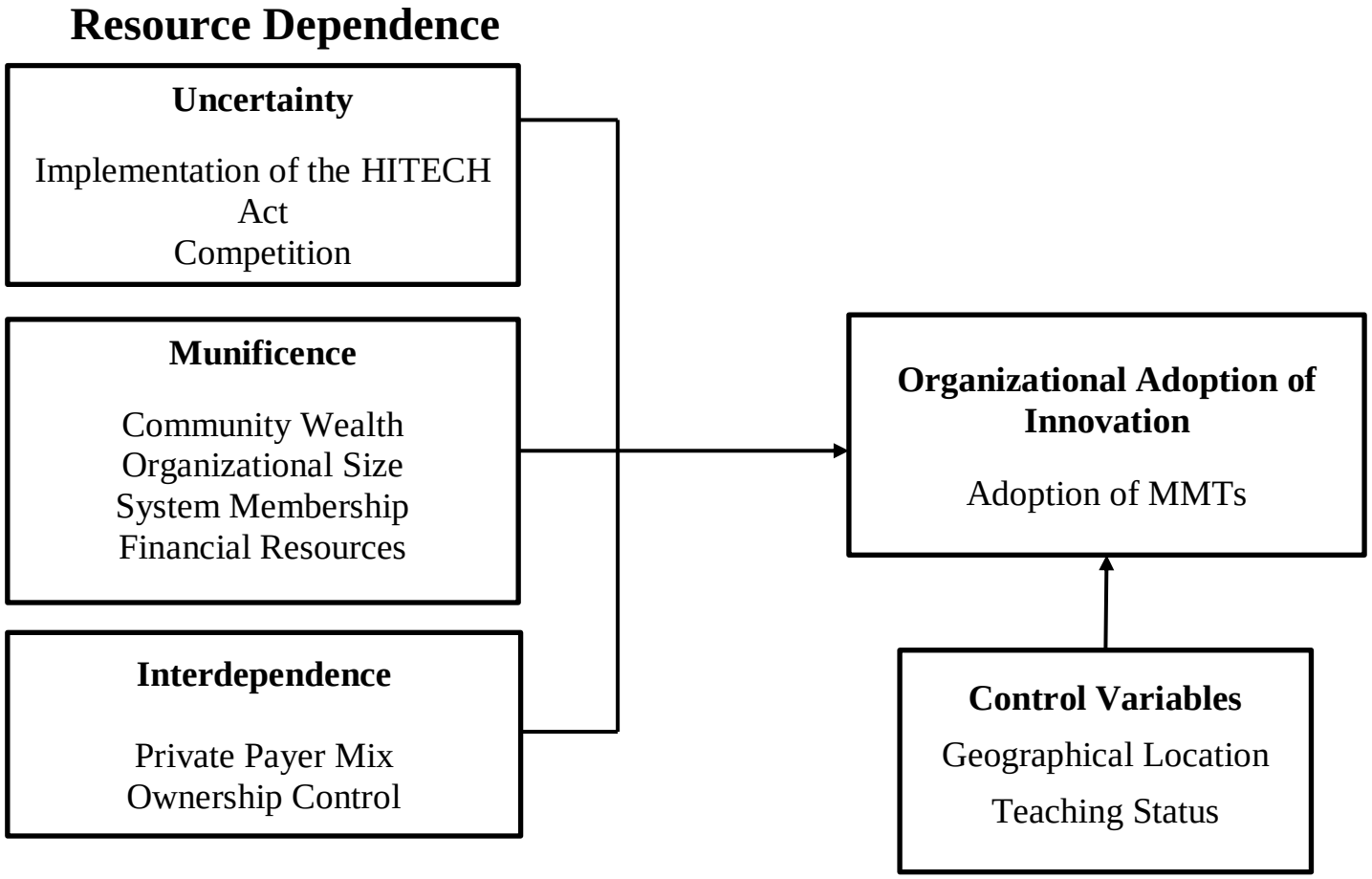

Figure 2: Conceptual Model of the Study

Key Constructs

The conceptual model, as shown in Figure 2, elucidates the theoretical framework and the key constructs of RDT that were used to derive the research hypotheses. The key behavioral construct of the study was the adoption of organizational innovation. This construct was operationalized as the adoption of MMTs by the acute care hospitals. The key causal constructs in this study were derived from the three constructs of RDT, which include uncertainty, munificence and interdependence.

Uncertainty was operationalized as the implementation of the HITECH Act and the degree of market competition. Munificence was operationalized as community wealth in the hospital market, organizational size, system membership and the availability of financial resources. Interdependence was operationalized as private payer mix and ownership control of the hospital.

Research Hypotheses

Based on the key constructs of RDT, the main empirical hypotheses proposed in this study were: 1) After the implementation of the HITECH Act, U.S. acute care hospitals will be more likely to adopt MMTs; and 2) organizational factors (organizational size, system membership, financial resources, private payer mix and ownership control) and environmental factors (market competition and community wealth in the hospital market) will be associated with the adoption of MMTs by the U.S. acute care hospitals. The specific research hypotheses that were empirically tested in this study are described in the ensuing paragraphs.

Uncertainty. As previously mentioned, RDT posits that organizations are dependent on the external environment to gain critical resources necessary for its survival (Pfeffer & Salancik, 1978). As the environment is dynamic, it may create uncertainties in the availability of these resources. Thus, organizations that are faced by a high degree of uncertainty in the environment

respond with strategic behaviors that will ensure the availability of resources and thereby, minimize the level of uncertainty in the environment ensuring the organization's chances of survival (Proenca, Rosko, & Zinn, 2000). Higher uncertainty in the environment leads to increased competition for the acquiring critical resources and thus organizations may adopt strategies to protect themselves from the external uncertainties and secure critical resources (Apenteng et al., 2015; Kazley & Ozcan, 2007). In the past, uncertainty in environment has been operationalized as competition in the market (Menachemi et al., 2012) and as regulatory pressures (Nayar, 2008). In this study, uncertainty was operationalized as the policy effect of the implementation of the HITECH Act as well as the degree of competition in the hospital market.

The implementation of the HITECH Act was a policy change in the environment, which affected all acute care hospitals in the U.S. As described previously in Chapter 2, the Act established monetary incentives to promote the adoption and 'meaningful use' of health IT, while penalizing those hospitals that did not comply with the objectives of the Act. The HITECH Act established its' objectives of meaningful use through three stages and the payment of the incentives for complying with Stage 1 began in 2011. The extent of the financial incentives, which started in 2011, included a $2 million base amount while the penalties, which began in 2015 started with a 1% penalty on Medicare reimbursement amounts, which then increases to 2% in 2016 and 3% in 2017 (Centers for Medicare and Medicaid Services, 2014c). Thus, this policy could have impacted the availability of resources, financial resources in this case, through the incentives and penalties, creating an uncertain environment for the hospital. If assumed to behave as rational, adaptive organizations, it is expected that the hospitals would react actively to this policy enactment. Hospitals, thus, may have adopted MMTs to gain the financial resources through the incentives and establish stability for their survival. Hospitals may also have acted as adaptive organizations and prepared to adopt all MMTs with the broader goal of improving patient safety.

H1: Hospitals will be more likely to adopt MMTs in the period after the implementation of the HITECH Act, all things being equal.

Organizations operating in a market with high degree of competition share the same limited resource pool (Pfeffer & Salancik, 1978). Hence, organizational survival depends on the allocation of these resources (Banaszak-Holl et al., 1996). In areas of high competition, health care providers need to distinguish themselves from the other providers to acquire critical resources. Thus, hospitals in highly competitive markets will attempt to differentiate themselves from others by adopting new technologies (Kazley & Ozcan, 2007). Further, in such areas of high competition, the patients may have a choice between multiple providers and would want to choose a provider based on the services as well as the quality of services provided. To attract such patients, a hospital may adopt new technologies known to improve the quality of services to attract patients. Thus, hospitals in areas of high competition will engage in strategic behaviors such as adoption of MMTs since these technologies can reduce medication errors and lead to increased patient safety, to maintain or increase their market share and improve their chances of survival. However, hospitals operating in areas that has less market competition may not be concerned about availability of resources and market share as they do not share their pool of resources with other hospitals in the market and patients do not have multiple choices.

H2: Hospitals located in markets with higher competition will be more likely to adopt MMTs, all things being equal.

Munificence. Munificence refers to the availability of resources for the hospital and impacts the organization's dependencies as well as strategic behaviors. It represents the abundance of resources external or internal to the hospital that are critical for its survival. An organization operating in an environment with abundant resources can acquire those resources needed for adoption of innovation with relative ease. Health services researchers have operationalized munificence as community wealth (Apenteng et al., 2015; Kazley & Ozcan, 2007; Nayar, 2008; Yeager et al., 2014), organizational size (Apenteng et al., 2015; Banaszak-

Holl et al., 1996; Kazley & Ozcan, 2007; Nayar, 2008; Zinn, Proenca, & Rosko, 1997), availability of financial resources (Kazley & Ozcan, 2007) and system membership (Alexander & Morrisey, 1989; Kazley & Ozcan, 2007).

In health services research, community wealth has been used to represent the availability of these external resources (Apenteng et al., 2015; Kazley & Ozcan, 2007; Nayar, 2008; Yeager et al., 2014). Hospitals operating in markets with higher community wealth have a larger patient base of privately insured people. These privately insured patients are sources of revenue to the hospitals. MMTs can be expensive and require an investment of financial capital from the hospital to purchase them (Classen & Brown, 2013). Hence, hospitals located in areas with higher income can generate revenue from their privately insured patient base. Such hospitals will hence have higher availability of financial resources to invest into MMTs. Further, since such patients can afford to be selective in their choice of hospitals, it is important for the hospitals to distinguish themselves from others in the market by providing higher quality of care. As described in Chapter 2, MMTs can improve the medication management process and through automation of the process and reduction of medication errors. Given that medication errors are the most common cause of medical errors (Leape et al., 1991) and the high prevalence of injuries arising out of medication errors and ADEs (Institute of Medicine, 2006), reducing medication errors can significantly improve patient safety and lead to higher quality of care.

H3: Hospitals located in markets with higher community wealth will be more likely to adopt MMTs, all things being equal.

Organizational size could be indicative of the availability of internal resources (Banaszak-Holl et al., 1996). Due to the availability of resources, larger organizations can remain autonomous and may also control the environmental resources. Larger hospitals have the financial capital as well as the organizational capability to invest in expensive technologies (Kazley & Ozcan, 2007). Previous research on adoption of innovations by hospitals has

established that larger hospitals were more likely to adopt innovations (Banaszak-Holl et al., 1996; Kazley & Ozcan, 2007; Zinn, Weech, & Brannon, 1998).

H4: Larger hospitals will be more likely to adopt MMTs, all things being equal.

Hospitals with a system membership are those belonging to a multi-hospital system comprising of a central headquarter hospital along with two or more affiliated hospitals (Alexander, Morrisey, & Shortell, 1986) and thus have access to a larger pool of resources through its member hospitals. System membership acts as a buffer to protect the member hospitals from uncertainties in the environment and reduces its dependencies on other external entities. Further, this affiliation also leads to sharing of knowledge as well as critical resources among the members of the system, thus making those members 'munificent' in terms of resources and giving them the ability to invest in and adopt technologies (Yeager et al., 2014).

H5: Hospitals that are part of a multi-hospital system will be more likely to adopt MMTs, all things being equal.

MMTs can be expensive and hence availability of financial resources is a major barrier in their adoption by the hospitals (Classen & Brown, 2013). Further, some complex new technologies may also require additional staff to operate them initially, or the financial resources to train the existing hospital staff (Menachemi & Brooks, 2006). The hospital may factor in this additional investment in the cost of the technology. Thus, a hospital with adequate financial resources can invest and purchase technologies. Those hospitals that do not have the financial means may not be able to adopt new technologies due to lack of internal resources.

H6: Hospitals with greater financial resources will be more likely to adopt MMTs, all things being equal.

Interdependence. Interdependence, as a construct of RDT, represents the dependencies of the organization on other external entities for resources which may be crucial for its survival (Pfeffer & Salancik, 1978). It is possible that organizations are more likely to comply with the demands of the external entities on which they are dependent. In the extant health services

literature, these interdependent relationships are represented by private payer mix (Yeager et al., 2014) and the ownership status of the hospitals (Apenteng et al., 2015; Banaszak-Holl et al., 1996; Kazley & Ozcan, 2007).

The private insurance agencies are one of the major payers for the hospitals. Additionally, patients with private insurance are the affluent patients. Hence, hospitals that serve higher proportions of patients with private insurance may be motivated to invest in innovations to provide better quality of care in order to maintain the flow of affluent resources and maintain the interdependence

H7: Hospitals with a higher proportion of private payer mix will be more likely to adopt MMTs, all things being equal.

The mission of the hospital defines its various strategic behaviors. For-profit hospitals operate with a profit maximization outlook and are dependent on their shareholders. Shareholders expect the hospitals to manage their investments and generate profits. Thus, for-profit hospitals may engage in innovations that would improve their efficiency and lower their costs and thereby, maximize their profits. For-profit hospitals also have the initial financial capital to make such investments (Clement & Grazier, 2001) and they may do so with the intention of maximizing profit in the long run. MMTs can effectively improve the efficiency of the medication management process and reduce costs arising out of medication errors. Thus, for-profit hospitals may see this as a good investment, aligning with their mission and with the demands on their shareholders.

H8: For-profit hospitals will be more likely to adopt MMTs as compared to public hospitals, all things being equal.

Summary of the Chapter

This chapter provided an overview of the competing theoretical perspectives on organizational strategic behavior, presenting both the adaptive and selective perspectives and then described the concept of innovation and adoption of innovations. Further, the second section of the chapter outlined the theoretical framework of this study. The basic tenets of RDT were discussed in detail and the conceptual model was developed based on the three key constructs of RDT. Additionally, the research hypotheses that were empirically tested in this study were described.

The ensuing Chapter 4 presents the study design, study sample and universe, measurement of the variables, their data sources as well as the analytical methods to answer the research question of this study.

CHAPTER FOUR: METHODOLOGY

This chapter focuses on the research methodology, including the research design, sources of data, study population and sample and the key measures for the dependent, independent and control variables included in this study. Further, the analytical strategy used to answer the research questions of this study is described. The chapter concludes by reviewing the methodological limitations as well as the ethical considerations of this study.

Research Design

The aim of this study was to examine the impact of the implementation of the HITECH Act on the adoption of MMTs by U.S acute care hospitals and the organizational and environmental correlates of the adoption of MMTs by U.S. acute care hospitals. The unit of analysis for this study was the individual acute care hospital in the U.S. and the period of the study was two years before and two years after the implementation of the HITECH Act (which came into effect in 2011) i.e., 2009 to 2013. The research design used to answer the research questions of this study was the interrupted time series design, which is a quasi-experimental design with a single group. A diagrammatic representation of this design is shown in Figure 3.

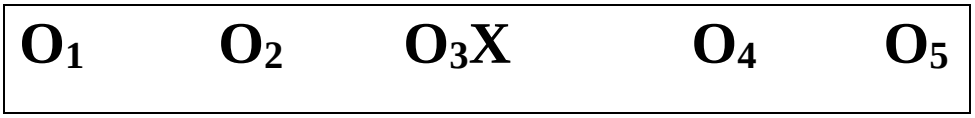

Figure 3: Research Design: Interrupted Time Series

O_1-O_5: Observations made two years before (2009 and 2010), during (2011) and two years after (2012 and 2013) the implementation of the HITECH Act

X: Implementation of the HITECH Act

There was only one group in this study design, which includes all the non-CAH, non-federal, acute care hospitals operating within the 50 U.S. States and the District of Columbia. The implementation of the HITECH Act in the year 2011 created a natural experiment, which impacted all the hospitals in the study sample. In the research design, this is represented by the

(X) symbol. Data from two years before the intervention (pre-HITECH Act) and two years after the intervention (post-HITECH Act) comprise the observations (O_1-O_5). Since there was only one group in this study with an intervention and multiple observations before and after the intervention, an interrupted time series design was the most appropriate design for this study. When an event interrupts the time series, or takes place within the time period of the measurements, this research design is able to examine the effects that occurred due to that event (Campbell & Stanley, 1963; Cherulnik, 2001).

A study with a quasi-experimental research design is easier to implement in natural settings and can be conducted using secondary databases (Cherulnik, 2001). This eliminates the artifacts that arise out of direct interaction between the researcher and the study participant that are common in experimental research (Cherulnik, 2001). Since this study examined pre-existing administrative databases of hospitals and not human participants, there was no interaction between the researchers and the study participants. Thereby, there were no threats to the study design due to reactive arrangements, pre-test sensitization, or linguistic/cultural bias.

The availability of multiple measures for the outcome of interest over time rendered strong internal validity to this study. These multiple measures revealed whether there were any temporal trends before the event of interest and if the trend was altered after the event occurred (Cherulnik, 2001). Hence, temporal trends did not pose a threat to the internal validity of the study (Cherulnik, 2001). Due to the single group study design, group composition effects did not pose a threat to internal validity. Thereby, the interaction between temporal effects and group composition effects could also be ruled out as a threat to internal validity. Extreme high or low baseline scores have the tendency to regress towards the mean and this may lead to the conclusion that the change in observation was due to the event but it was in fact due to regression toward the mean (Cherulnik, 2001). In an interrupted time series design, multiple measures enable the detection of these effects of regression towards the mean, separately from the effect of the event

(Cherulnik, 2001). Thus, there were no threats to this study design due to statistical regression effects. Further, this study was a retrospective study using secondary data sources over multiple years which contained all the non-CAH, non-federal, acute care hospitals in the U.S. and hence there were no threats due to selective sample attrition in this study. However, this research design was not able to control for the extraneous events that may be a threat to the internal validity of the study (Cherulnik, 2001). It is possible that some other extraneous event may have occurred at the same time as the implementation of the HITECH Act that could have impacted the outcome of interest and thereby overestimated or underestimated the effect of the Act.

The study universe was all non-CAH, non-federal, acute care hospitals operating within the 50 U.S. States and the District of Columbia. The study population consisted of all non-federal, non-CAH acute care hospitals operating within the 50 U.S. States and the District of Columbia and reporting to the HIMSS Analytics Database. The study sample was derived from the Healthcare Information and Management Systems Society (HIMSS) Analytics Database and consisted of all non-CAH, non-federal, acute care hospitals of the study population that merged across all three secondary data sources used in this study, had no missing values for the dependent and independent variables of interest and were observed for all five years of the study duration. In order to ensure representativeness of the research sample, statistical tests were used to compare the characteristics of the study sample with the study population. As described in detail in Chapter 5, no significant differences were observed between the study sample and study population. Hence, there were no threats due to non-representative research sample. The study examined the effects of an enactment of a policy in the real-world, eliminating the threats to external validity due to non-representative research context.

This study used panel data with lagged data for the independent variables. Panel data consists of information on the same units followed over a given time period (Wooldridge, 2015). The data for the dependent variable were examined from 2009 to 2013, while the data for the

independent variables of organizational and environmental factors as well as the control variables were examined from 2008 to 2012, representing a one-year lag. Panel data provides various advantages over cross-sectional data or even pooled cross-sectional data (Wooldridge, 2015). Panel data allows for assessing variations between units as well as within units over time (Wooldridge, 2015). Availability of multiple measures on the same units over time allows controlling for unobserved characteristics, thereby producing consistent estimates while controlling for omitted variable bias (Wooldridge, 2015). Further, the lagging of the independent variables addresses the issue of potential endogeneity of the variables.

Data Sources

The independent, dependent and control variables were derived from the following secondary databases:

1. Healthcare Information and Management Systems (HIMSS) Analytics Database: The HIMSS Analytics Database, formerly known as Dorenfest Data, contains data from over 5,300 hospitals in the U.S. Data were available from the Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation at Chicago, Illinois (The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, 2010). The data includes the Dorenfest 3000+ Databases™, the Dorenfest Integrated Healthcare Delivery System Databases™ and previous editions of the HIMSS Analytics® Database (The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, 2010). This dataset includes information on hospital characteristics such as patient revenue, ownership control, hospital location, etc. as well as software, hardware and infrastructure installed in the facilities and future software and hardware purchase plans for the facilities (The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation, 2010). The HIMSS Analytics databases for the years 2008 to 2013, available from the Dorenfest Institute, were used in this study. Independent variables of size, teaching status and system membership were identified from the database for the years

2008 to 2012, while the dependent variable of adoption of MMTs were identified from the database for the years 2009 to 2013.

2. Healthcare Cost Report Information System (HCRIS): The HCRIS is maintained by the CMS and includes information on facility characteristics, utilization data, costs and charges, Medicare settlement data and financial statement data (Centers for Medicare and Medicaid Services, 2016c). The HCRIS dataset was merged with the HIMSS Analytics Database using the Medicare Provider Number. Certain facility characteristics such as inpatient days, operating margin and ownership control were obtained from this dataset for the years 2008 to 2012.
3. Area Health Resource File (AHRF): The AHRF contains county-level data and has current as well as historic data for more than 6,000 variables for each county in the nation (Health Resources and Services Administration, 2016). The AHRF provides information on "health facilities, health professions, measures of resource scarcity, health status, economic activity, health training programs and socioeconomic and environmental characteristics" (Health Resources and Services Administration, 2016). For the purposes of this study, the market area of the hospital was defined as the county within which the hospital is located (Garnick, Luft, Robinson, & Tetreault, 1987). The county location of the hospital was used to merge the HIMSS Analytics Database with the AHRF database in order to examine the environmental factors in which the hospital is functioning. In this study, the county where the hospital is located was used to calculate the measure of market competition as well as identify the rurality of the geographical location of the hospital

Study Universe, Population and Sample

The unit of analysis for this study was the individual acute care hospital in the U.S. The universe for this study included all the non-CAH, non-federal, acute care hospitals operating within the 50 U.S. States and the District of Columbia. This universe excluded the hospitals with specialized functions such as orthopedic, psychiatric or children's hospitals. The universe also

excluded federally-owned hospitals such as the Veteran's Affairs Hospitals, Military Hospitals and Public Health Indian Service Hospitals as the operation of these hospitals differs from non-federal hospitals in terms of their financing and management structure, as well as their policies and patient populations. This study universe also excludes CAHs as they are certified under a different set of conditions than acute care hospitals (Scalise, 2004). Further, this population also excluded the hospitals located in the U.S. territories (American Samoa, Guam, Northern Mariana Islands, Puerto Rico and U.S. Virgin Islands).

The study population consisted of all the non-CAH, non-federal, acute care hospitals operating within the 50 U.S. States and the District of Columbia that reported data to the HIMSS Analytics Database. The HIMSS Analytics Database contains data on all non-federal hospitals in the U.S. (Swanson, 2006). The study population consisted of 3,452 non-CAH, non-federal, acute care hospitals in 2009, 3,435 in 2010, 3,409 in 2011, 3,407 in 2012 and 3,396 in 2013 obtained from the HIMSS Analytics Database. This data from each year was merged with the HIMSS Analytics database from the respective previous year using a unique identification number in the HIMSS Analytics Database, which remained the same for each unique hospital over the years. After this merging, 76 observations were dropped off from the dataset of year 2009, 32 from 2010, 27 from 2011, 38 from 2012 and 20 from 2013. This dataset was merged with the HCRIS data of the previous year using the Medicare Provider Number. In the HCRIS data, only those hospitals that reported data covering 270 fiscal days or more were retained. After this merging, 363 observations were dropped off from the dataset of year 2009, 342 from 2010, 332 from 2011, 285 from 2012 and 312 from 2013. This dataset was then merged with the AHRF data of the previous year by matching the county of the hospital location obtained from the HCRIS data to the county name variable in the AHRF data. This merging with the AHRF data did not drop any observations. Further, hospitals with missing data for any of the study variables were excluded. This led to observations on 48 hospitals being dropped from the dataset of the year 2009, 50 from

2010, 43 from 2011, 43 from 2012 and 40 from 2013. Further, only those hospitals that were observed for all years of the study period were retained in the final empirical sample. Thus, the final empirical sample consisted of 13,690 observations from 2,738 unique hospitals. The dataset was a balanced panel i.e., all the hospitals were observed for the entire study period of five years. In order to ensure that the study sample was representative of the study population, differences in the independent and dependent variable measures between the study population and sample were examined.

Key Measures

This section provides the description and measures of the variables in this study, derived from the constructs of resource dependence theory (RDT), as presented in the conceptual model. For the purpose of this study, the market area of the hospital was defined as the county within which the hospital was located. This definition for the hospital market has been used extensively in previous research (Alexander & Morrisey, 1989; Apenteng et al., 2015; Rosko, Chilingerian, Zinn, & Aaronson, 1995; Zinn et al., 1997; Zinn et al., 1998). Further, Garnick et al. noted that for the purpose of measuring competition, the definition of the market as a county or as a 15-mile radius area of the hospitals did not make a significant difference (Garnick et al., 1987). Table 1 provides a summary of constructs, variables and their measures and data sources.

Table 1: Constructs, Variables and Measurements and Data Sources

Construct	Variable	Measure	Description of Measure	Data Source
Behavioral Construct	**Dependent Variable**			
Organizational Innovation	Adoption of MMTs	Global measure of adoption MMTs (GLOBAL_ADOPT)	GLOBAL_ADOPT=total number of MMTs adopted	2009-2013 HIMSS
		Adoption of MU MMTs (MU_MMT)	MU_MMT=1, if adopted CPOE, CDSS and eMAR together; 0 otherwise	2009-2013 HIMSS
		Adoption of CLMM (CLOSEDLOOP)	CLOSEDLOOP=1, if adopted; 0 otherwise	2009-2013 HIMSS
		Adoption of ordering technology (ORDER)	0= low adoption; 1= medium adoption; 2=high adoption	2009-2013 HIMSS
		Adoption of transcribing technology (TRANSCRIBE)	0= low adoption; 1= medium adoption; 2=high adoption	2009-2013 HIMSS
		Adoption of dispensing technology (DISPENSE)	0= low adoption; 1= medium adoption; 2=high adoption	2009-2013 HIMSS
		Adoption of administration technology (ADMINISTER)	0= low adoption; 1= medium adoption; 2=high adoption	2009-2013 HIMSS
Causal Construct	**Independent Variables**			
Uncertainty	Policy Enactment	Implementation of the HITECH Act (PRE_HITECH and POST_HITECH)	PRE_HITECH=1, if the time period of data was 2009 or 2010; 0 otherwise POST_HITECH=1, if the time period of data was 2012 or 2013; 0 otherwise	CMS

	Competition	Herfindahl-Hirschman Index (HHI)	HHI= sum of squares of the total inpatient days in the hospital annually/ total inpatient days in all hospitals in that county	2008-2012 HCRIS and 2008-2012 AHRF
Munificence	Community Wealth	Household Income (INCOME)	INCOME=Average household income in the county	2008-2012 AHRF
	Size	Organizational Size (SIZE)	SIZE=Total number of Beds set up and staffed	2008-2012 HIMSS
	System Member	System Membership (SYSTEM)	SYSTEM=1, if the hospital is a member of a system; 0 otherwise	2008-2012 HIMSS
	Financial Resources	Operating Margin (OPERATING_MARGIN)	OPERATING_MARGIN= (Operating Revenue-Operating Expenses)/Operating Revenue	2008-2012 HCRIS
Interdependence	Private Payer Mix	Private Payer Mix (PRIVATE_PAYER)	PRIVATE_PAYER= Number of private insurance inpatient days/Total number of inpatient days	2008-2012 HCRIS
	Ownership Control	For-profit ownership (FOR_PROFIT)	FOR_PROFIT=1, if for-profit hospital; 0 otherwise	2008-2012 HCRIS
		Non-Profit ownership (NON_PROFIT)	NON_PROFIT=1, if non-profit hospital; 0 otherwise	2008-2012 HCRIS
Control Variables				
		Geographical Location (METRO_ADJ, RURAL)	METRO_ADJ=1, if hospital located in a county with RUCC Codes 04, 06 (Metropolitan adjacent counties); 0 otherwise RURAL=1, if hospital located in a county with RUCC Codes 05, 07, 08, 09 (Rural counties); 0 otherwise	2008-2012 AHRF

		Member of Council of Teaching Hospital of the Association of American Medical College (TEACH)	TEACH=1, if a member; 0 otherwise	2008-2012 HIMSSAnalytics Database

Dependent Variables

The behavioral construct of adoption of innovation was operationalized as the adoption of MMTs. Adoption of MMTs was specifically measured as: (1) the global adoption of all MMTs, (2) adoption of MU MMTs (CDSS, CPOE and eMAR), (3) adoption of CLMM and as the adoption of technology for each of the steps of the medication management process viz., (4) ordering technology, (5) transcribing technology, (6) dispensing technology and (7) administration technology. Data on the adoption of 12 MMTs were available from the HIMSS Analytics Database for the years 2009 to 2013. These 13 technologies are: Computerized Physician Order Entry (CPOE), Clinical Decision System Software (CDSS), in-house transcription software, bar-coding at dispensing, Radio Frequency Identification (RFID) at dispensing, robot-filling for prescriptions, Automated Dispensing Machine (ADM), pharmacy management system, bar-coding at medication administration, RFID at medication administration, Electronic Medication Administration Record (eMAR), smart pumps and CLMM. The descriptions and functions of each of these technologies were provided in detail in Chapter 2.

As described earlier in Chapter 2, these different technologies are used for automation of the four steps of the medication management process (ordering, transcribing, dispensing and administration). CPOE and CDSS are used at the ordering step; in-house transcription software and eMAR are used at the transcribing step; bar-coding at dispensing, RFID at dispensing, robot-filling for prescriptions, ADMs and pharmacy management system are used at the dispensing step; and bar-coding at medication administration, RFID at medication administration, eMAR and smart pumps are used at the administration step. The definition of adoption is described in the ensuing paragraph.

To measure the dependent variable of adoption of MMTs, the adoption status of each technology needed to be defined. In the HIMSS dataset, the adoption status of five technologies (CPOE, CDSS, in-house transcription software, pharmacy management system and eMAR) was categorized as 'Contracted/Not Yet Installed', 'Installation in Process', 'Live and Operational', 'Not Automated', 'Not Reported', 'Not Yet Contracted', 'Service Not Provided' and 'To be Replaced'. This study defined adoption as the hospitals' reporting their status as 'Live and Operational'. This conservative measure of adoption has been used in previous studies using the HIMSS Analytics Database (Furukawa et al., 2008; Kazley & Ozcan, 2007). Data on the adoption of the remaining seven technologies was categorized in the dataset as whether or not the facility uses the technology. Hence, adoption of these technologies was defined as the response of 'yes' to the question of their use in that facility.

Further, data on the adoption of CLMM were also available in the dataset. The CLMM system is an inter-connected environment that integrates each of the four steps of the medication management process (Healthcare Information and Management Systems Society, 2010). This system is not a separate technology used at a specific step of the medication management process but it is a process in the hospital that integrates the different steps of medication management. In the HIMSS Analytics Database, adoption of closed-loop medication administration at point of CLMM was a dichotomous variable and was measured as through the responses of 'yes' or 'no' to depict whether or not it was adopted. Table 2 provides a summary of the categorization of the technologies for the different steps of the medication management process and the measurement of their adoption.

Table 2: MMTs used in the Medication Management Process and their Adoption Definitions

Step of Medication Management	Technology	Adoption defined as 'live and operational'	Adoption defined as 'yes' response to use of technology
Ordering	1. Computerized Physician Order Entry (CPOE)	x	
	2. Clinical Decision Support System (CDSS)	x	
Transcribing	3. In-house Transcription software	x	
	4. Electronic Medication Administration Record (eMAR)	x	
Dispensing	5. Bar-coding at Dispensing		x
	6. RFID at Dispensing		x
	7. Robots		x
	8. Automated Dispensing Machines (ADMs)		x
	9. Pharmacy Management System	x	
Administration	10. Bar-coding at Administration		x
	11. RFID at Administration	x	
	12. Electronic Medication Administration Record (eMAR)		x
	13. Smart Pumps		x
All steps	14. CLMM		x

Measurement of Dependent Variables

After the adoption status of each technology was defined, the next step was to use this adoption status to define the measurement of the dependent variable of adoption of MMTs. The dependent variable was measured in seven ways:

1) Global adoption of MMTs (GLOBAL_ADOPT): a count of the total number of MMTs that were adopted by the hospital.
2) Adoption of MU MMT (MU_MMT): dichotomous variable representing whether or not the hospital adopted all three MU MMTs (CPOE, CDSS, eMAR).
3) Adoption of CLMM (CLOSEDLOOP): dichotomous variable representing whether the hospital adopted closed-loop medication administration at point of care or not.

4) Adoption of ordering technology (ORDER): a categorical variable representing the level of adoption of ordering technologies defined as low adoption (adoption of no technology), medium adoption (adoption of one technology) and high adoption (adoption of both technologies).
5) Adoption of transcribing technology (TRANSCRIBE): a categorical variable representing the level of adoption of transcribing technologies defined as low adoption (adoption of no technology), medium adoption (adoption of one technology) and high adoption (adoption of both technologies).
6) Adoption of dispensing technology (DISPENSE): a categorical variable representing the level of adoption of dispensing technologies defined as low adoption (adoption of less than three technologies), medium adoption (adoption of three technologies) and high adoption (adoption of more than three technologies).
7) Adoption of administration technology (ADMINISTER): a categorical variable representing the level of adoption of administration technologies defined as low adoption (adoption of less than two technologies), medium adoption (adoption of two technologies) and high adoption (adoption of more than two technologies).

Independent Variables

The causal constructs of the study were the key constructs of resource dependence theory and were represented as uncertainty, munificence and interdependence. The operationalization and measurement of these constructs are discussed below.

Operationalizing Uncertainty. Uncertainty refers to the instability in the environment that impacts the availability of resources for the organizations (Pfeffer & Salancik, 1978). This construct of uncertainty was operationalized as the implementation of the HITECH Act and the

degree of market competition. A change in policy creates an uncertainty for the organization to access resources (Nayar, 2008). The HITECH Act was enacted to encourage the adoption and use of technology for improved outcomes. The Act established incentives that were implemented in the year 2011, as well as and penalties for the hospitals. It thus represents an uncertainty in the hospital environment with respect to availability of financial resources through the incentives and penalty. Further, competition in the hospital market represents uncertainty for the hospital to acquire the resources shared by the same pool of competing hospitals (Kazley & Ozcan, 2007; Yeager et al., 2014). The measurements of these variables are described below.

1) Implementation of the HITECH Act (PRE_HITECH and POST_HITECH): The variable was measured using dummy variables for the time period of data with respect to the year 2011, in which the HITECH Act first went into effect. These dummy variables will be represented as PRE_HITECH (1 if year was 2009 or 2010, 0 otherwise) and POST_HITECH (1 if year was 2012 or 2013, 0 otherwise), with period of 2011 being the reference group.
2) Competition (HHI): The Herfindahl-Hirschman Index (HHI) represents competition in the hospital environment and was computed as the sum of squares of the total inpatient days in the hospital annually divided by the total inpatient days in all hospitals in that county. HHI ranges from a scale of 0 to 1, with 0 capturing perfect competition and 1 capturing perfect monopoly. Hence, lower HHI implied higher competition. Data on inpatient days were obtained from the HCRIS database for the years 2008 to 2012.

Operationalizing Munificence. Munificence refers to the abundance of resources available to the organization (Pfeffer & Salancik, 1978). In accordance with the literature, munificence was operationalized as community wealth, organizational size, system membership and financial resources (Kazley & Ozcan, 2007; Yeager et al., 2014). The measurements of these variables are described below.

1) Community Wealth (INCOME): Community wealth was measured by the average household income of the county in which the hospital is located in. Data on the household income in the county were obtained from the AHRF database for the years 2008 to 2012.
2) Size (SIZE): Hospital size was measured by the number of beds set up and staffed. Data were obtained from the HIMSS Analytics Database for the years 2008 to 2012.
3) System Membership (SYSTEM): System membership was measured by whether or not the hospital is a participant of a multi-hospital system. Data for this variable were obtained from the HIMSS Analytics Database for the years 2008 to 2012.
4) Financial Resources (OPERATING_MARGIN): Financial resources of the hospital were measured by operating margin, which was computed by dividing the net operating income (operating revenue-operating expenses) by the operating revenue. Data for this variable were obtained from the HCRIS database for the years 2008 to 2012.

Operationalizing Interdependence. Interdependence is represented by the dependency of the organization on external entities for acquiring resources. In consistence with previous literature, interdependence was operationalized as the private payer mix (Yeager et al., 2014) and the ownership control of the hospital (Apenteng et al., 2015; Nayar, 2008; Yeager et al., 2014). The measurements of these variables are described below.

1) Private Payer Mix (PRIVATE_PAYER): Private payer mix was measured as the proportion of the inpatient days covered by private insurance as compared to the total number of inpatient days for the hospital. This variable was obtained from the HCRIS database for the years 2008 to 2012.
2) Ownership Control (FOR_PROFIT, NON_PROFIT): For-profit ownership control of the hospital was measured as a dummy variable which indicated whether the hospital was a for-profit hospital or otherwise. Non-profit ownership control of the hospital was measured as a

dummy variable which indicated whether the hospital was a non-profit hospital or otherwise. In this case, the reference group for ownership control was public ownership. This information was obtained from the HCRIS database for the years 2008 to 2012.

Control Variables

Other organizational and environmental characteristics of the hospital that may have had an impact on the adoption of MMTs were controlled for in this study. These factors were represented by geographical location and the teaching status of the hospital. The measurements of these variables are described below.

1) Geographical Location (METRO_ADJ and RURAL): Rural-Urban Continuum Codes (RUCC) were used to identify the geographic location of the county in which the hospital was located in. RUCC codes can be categorized as metropolitan (RUCC Codes 01, 02, 03), metropolitan adjacent counties (RUCC Codes 04, 06) and rural counties (RUCC Codes 05, 07, 08, 09). This study adjusted for the rural/urban location of the hospital, which was measured through a dummy variable for metropolitan adjacent counties (METRO_ADJ) and a dummy variable for rural counties (RURAL), with the metropolitan counties being the reference group. This information was obtained from the AHRF for the years 2008 to 2012.
2) Teaching Status (TEACH): Teaching status of the hospital was represented by the hospital's membership in Council of Teaching Hospital (COTH) of the Association of American Medical Colleges (White, Cochran, & Patel, 2002). This variable was measured by a dummy variable which indicated if the hospital was a member of COTH or otherwise. Data for this variable were obtained from the HIMSS Analytics Database for the years 2008 to 2012.

Data Analysis Approach

The empirical model for the study is specified as follows:

$Adoption_{it} = \beta_0 + \beta_1 PRE\_HITECH_t + \beta_2 POST\_HITECH_t + \beta_3 Env_{it} + \beta_4 Org_{it} +$

$\beta_5 \gamma_t + + \alpha_i + \varepsilon_{it}$ *(Model 1)*

In this model,

i represents the hospital and *t* represent time

$Adoption_{it}$ refers to the adoption status of technology in hospital *i* at time *t*

PRE_HITECH_t is a dummy variable for time before the implementation of the HITECH Act (PRE_HITECH=1 for the years 2009 and 2010, 0 otherwise)

$POST\_HITECH_t$ is a dummy variable for time after the implementation of the HITECH Act (POST_HITECH=1 for the years 2012 and 2013, 0 otherwise)

Env_{it} represents the vector of environmental variables for hospital *i* at time *t*

Org_{it} represents the vector of organizational variables for hospital *i* at time *t*

γ_t refers to the year dummies that account for the secular trends, irrespective of the change in policy

α_i refers to the unobserved hospital-specific effects

ε_{it} is the error term

Data analyses were conducted using SAS 9.4 and Stata 14 software (SAS Institute Inc., Cary, North Carolina; StataCorp LP., College Station, TX). Statistical significance was assessed at a two-sided p-value of <0.05. A p-value of <0.10 was considered to be marginally significant. Descriptive analyses and multivariate analyses were conducted as described below.

Descriptive Analyses

Descriptive statistics such as frequencies and cross-tabulations for categorical variables and means, standard deviations, minimum and maximum for continuous variables were used to describe the characteristics of the hospitals in the study sample and the population. The variables were also checked for missing data, outliers, skewness and kurtosis and were appropriately transformed. T-tests were used to compare the characteristics of the study sample with the study population. Pearson's correlation coefficients were used to test the correlations between all the independent variables in the study and to detect any issue of multicollinearity.

Multivariate Analyses

Since panel data consists of observations from the same set of units over multiple years, there is correlation between these observations (Wooldridge, 2015). Thus, it is important to account for the correlation structure when conducting any analysis. Analytical methods that can handle correlated data include fixed effects, random effects and mixed effects/multi-level models. A description of each of these methods is provided below:

1) Fixed effects model: A fixed effects model can control for the time-invariant variables in the model and can assess the group and time effects (Wooldridge, 2015). Thus, fixed effects models should when researcher is interested in analyzing the impact of variables that are changing over time and should not be used when the key independent variables that specific to the hospital are time-invariant. A fixed effects model is represented as:

$$Y_{it} = \beta_0 + \beta_0 X_{it} + \alpha_i + \varepsilon_{it}$$

Here,

Y_{it} is the dependent variable

X_{it} is the independent variable

α_i represents the un-observed hospital specific characteristics

ε_{it} is the idiosyncratic error term

The un-observed hospital specific characteristics (α_i) are the fixed effects components that captures the unobserved heterogeneity across hospitals that are fixed over time. When using fixed effects model, it is assumed that α_i impacts the dependent and independent variables, which is why they should be controlled (Wooldridge, 2015). A fixed effects model allows for correlation between the hospital-specific error term α_i and the independent variables.

$$Cov(X_{it}, \alpha_i) \neq 0$$

Hence, the time-invariant explanatory variables are swept away in a fixed effects estimation. Another assumption is that the idiosyncratic error-term ε_{it} is uncorrelated with the independent variables across all time periods (Wooldridge, 2015). There are three approaches to fixed effects estimation: (a) within transformation, (b) least squares dummy variable estimator and (c) between estimator (Wooldridge, 2015).

In the within transformation approach, time-demeaned data for the independent and dependent variables are used, which eliminates the unobserved effect α_i (Wooldridge, 2015). In the least squares dummy variable estimation, dummy variable for each cross-sectional observation is included in the model along with the independent variables (Wooldridge, 2015). Thus, for N repeated observations, N-1 dummy variables will be included in the model. These dummy variables account for the un-observed time-invariant hospital-specific characteristics that may impact the outcome of interest. If the panel data has large N and small T, which is the case in this study, the number of explanatory variables would make it challenging to carry out the regression (Wooldridge, 2015). In the between estimator, time averages for the independent and the dependent variables are used and thereby limiting the

analysis to a cross-sectional regression (Wooldridge, 2015). The between estimator thus uses N observations, instead of the N*T observations that are used in the first two approaches. This estimator thereby ignores the trend in variables over time.

Since the dataset used in this study has large N and small T, the least squares dummy variable estimator was not suitable. Further, trends over time could not be ignored in this study and hence, the between estimator was not appropriate. Thereby, the within transformation approach was used to assess the fixed effects model in this study.

2) Random effects model: The random effects model is used when the un-observed effect α_i is uncorrelated with each explanatory variable in all time periods (Wooldridge, 2015).

$$Cov(X_{it}, \alpha_i) = 0$$

In such a case, inefficient estimators will be produced if transformation is used to eliminate α_i. All the assumptions of the fixed effects model apply to the random effects model, with the exception that α_i should be independent of all explanatory variables in all time periods (Wooldridge, 2015). Since α_i is uncorrelated with all explanatory variables, it is possible that the coefficients could be estimated consistently with pooled ordinary least square (OLS) regression with time dummies. However, the pooled OLS estimator ignores the serial correlations in the error terms across time and hence produces incorrect standard errors and test statistics (Wooldridge, 2015). The random effects estimator, on the other hand, uses the generalized least squares (GLS) method to account for the serial correlation (Wooldridge, 2015). Wooldridge (2013) suggests when applying fixed effects and random effects models, it may be also beneficial to compute the pooled OLS estimates for comparison (Wooldridge, 2015). This comparison can help examine the biases that are caused when α_i is left entirely in the error term (pooled OLS) or partially in the error term (random effects model).

3) Specification Tests: The Hausman test is used to choose the appropriate model between the random effects and fixed effects model (Wooldridge, 2015). The null hypothesis of the Hausman test is that α_i is uncorrelated with the explanatory variables (Wooldridge, 2015). Thus, the random effects model was used if the null hypothesis was not rejected and the fixed effects model was used if the null hypothesis was rejected (Wooldridge, 2015). If the Hausman test rejected the fixed effects model and a random effects model is considered appropriate, the Breusch-Pagan Lagrange multiplier test was used to evaluate whether the random effects model or the pooled OLS model yielded consistent estimates and one of the models were chosen based on the results of the test (Wooldridge, 2015). However, if the Hausman test did not reject the null hypothesis and a fixed effects model was deemed appropriate, a mixed effects model was considered. The rationale behind choosing a mixed effects model over a fixed effects model is described below.
4) Mixed effects model: In the fixed-effects model, all the time-invariant variables would be excluded from the model (Wooldridge, 2015). Some of the key independent variables in this study were not expected to vary over time, such as ownership control, system membership, etc. A mixed effects model allows a researcher to assess both fixed and random effects, thereby allowing the inclusion of the time-invariant effects as well as the random effects (Rabe-Hesketh & Skrondal, 2012). This model allows the researcher to account for hierarchies or multi-levels in the dataset (Rabe-Hesketh & Skrondal, 2012). The hierarchical data structure is true for this study, as both the organizational-level factors as well as county-level factors were examined. Hence, between a fixed effects model and a mixed effects model, the latter was appropriate for this study in order to be able to examine the time-invariant variables and also account for the hierarchical data structure. Different mixed effects models were examined such as models with hospital random intercept only, hospital

and county-level random intercepts, hospital and state-level random intercepts and hospital, county and state-level random intercepts. The models with the lowest Akaike Information Criterion (AIC) values were chosen for each measure of the dependent variable (Akaike, 1974).

There were seven measures of the adoption of MMTs in this study: GLOBAL_ADOPT, CLOSEDLOOP, MU_MMT, ORDER, TRANSCRIBE, DISPENSE and ADMINISTER. Of these, one outcome of interest (GLOBAL_ADOPT) was a count variable and hence a Poisson regression model was appropriate. Two measures of adoption of MMTs (CLOSEDLOOP and MU_MMT) were dichotomous variables and hence, logistic regression models were appropriate. For Poisson and logistic regression models, specification of fixed effects, random effects and mixed effects is possible. The remaining four outcomes of interest (ORDER, TRANSCRIBE, DISPENSE and ADMINISTER) were categorical variables with three levels. Hence, multinomial logistic regression models were appropriate. For the multinomial logistic regression models, fixed effects specification alone was not possible as its use is limited in practice due to unfeasible computations (Pforr, 2011). Further, the analytical dataset was multi-level in nature i.e., the dataset consisted of hospitals nested within counties, which were further nested within states and both organizational and count-level factors were used in the regression analyses. Hence given this multi-level nature of the dataset, a mixed effects model for the multinomial logistic regression was used.

Methodological Limitations

There were certain methodological limitations in this study that must be considered. The absence of the control group in the study design is an important limitation of this study. With no comparison group, it is not possible to control for other extraneous events that may be related to the adoption of MMTs. Further, due to the absence of a control group, the policy effects could not

be separated from the effects of secular trends. Also, this study may have missed on certain explanatory variables such as hospital leadership characteristics that may influence the adoption of MMTs due to unavailability of data.

Ethical Considerations

Since this study used secondary data sources at the organizational-level and did not include human participants or patient-level data, a review by the Institutional Review Board was not required.

Summary of the Chapter

This chapter described the research design, data sources, study population and the study sample, as well as the key measures for the dependent, independent and control variables used in this study. The use of a quasi-experimental interrupted time series design is a strength of this study. Further, two data sources were merged to obtain the variables of the study. Analytical strategies for panel data such as fixed effects, random effects and mixed effects models were discussed and the rationale for using the final model was discussed. Further, the methodological limitations as well as the ethical considerations were discussed. The ensuing Chapter 5 presents the results of the study and the findings and implications of the study are discussed in Chapter 6.

CHAPTER FIVE: RESULTS

This chapter presents the results of the empirical analyses of this study in two sections: Descriptive Analyses Results and Multivariate Regression Analyses Results. The Descriptive Analyses section includes the descriptive statistics of the organizational and environmental characteristics of the study population and sample, trends in the outcomes of interest from the pre-HITECH period to the post-HITECH period and a correlation analysis between the independent variables used in the study. In the next part comprising of the multivariate regression analyses, seven empirical models examining the organizational and environmental correlates of the adoption of MMTs are presented. These models are:

1) Global Adoption of MMTs
2) Adoption of MU MMTs
3) Adoption of CLMM
4) Adoption of Ordering Technologies
5) Adoption of Transcribing Technologies
6) Adoption of Dispensing Technologies
7) Adoption of Administration Technologies

Descriptive Analyses Results

The aim of this study was to examine the impact of the HITECH Act on the adoption of MMTs by U.S. acute care hospitals and the organizational and environmental factors associated with this adoption. The study population consisted of all non-CAH, non-federal, acute care hospitals operating within the 50 U.S. States and the District of Columbia. The dependent variable measures were obtained from 2009 to 2013 and the independent variables were measured from 2008 to 2012, representing a one-year lag for the independent variables. This study period was chosen since the Stage 1 of the HITECH Act came into effect in 2011 i.e., the HITECH Act was implemented in the year 2011. Hence, the study examined data from two years before and two years after this implementation to examine the early impact of the Act on adoption etc.

The study population consisted of 3,452 non-CAH, non-federal, acute care hospitals in 2009, 3,435 in 2010, 3,409 in 2011, 3,407 in 2012 and 3,396 in 2013 obtained from the HIMSS Analytics Database. This data from each year was merged with the HIMSS Analytics database from the respective previous year using a unique identification number in the HIMSS Analytics Database, which remains the same for each unique hospital over the years. After this merging, 76 observations were dropped off from the dataset of year 2009, 32 from 2010, 27 from 2011, 38 from 2012 and 20 from 2013. This dataset was merged with the HCRIS data of the previous year using the Medicare Provider Number. In the HCRIS data, only those hospitals that reported data covering 270 fiscal days or more were retained. After this merging, 363 observations were dropped off from the dataset of year 2009, 342 from 2010, 332 from 2011, 285 from 2012 and 312 from 2013. This dataset was then merged with the AHRF data of the previous year by matching the county of the hospital location obtained from the HCRIS data to the county name variable in the AHRF data. This merging with the AHRF data did not drop any observation. Further, hospitals with missing data for any of the study variables were excluded. This led to observations on 48 hospitals being

dropped from the dataset of the year 2009, 50 from 2010, 43 from 2011, 43 from 2012 and 40 from 2013. Further, only those hospitals that were observed for all years of the study period were retained in the final empirical sample. Thus, the final empirical sample consisted of 13,690 observations from 2,738 unique hospitals. Table 3 summarizes the steps of the creation of the analytical study sample and the number of hospitals in the population and the sample for all the years.

Table 3: Creation of Study Sample

Sample Creation Step	2009	2010	2011	2012	2013	Total
Total Number of non-federal Hospitals in the HIMSS Analytics Database	5,237	5,283	5,339	5,467	5,467	26,793
Total Number of Acute Care Hospitals	4,743	4,737	4,739	4,754	4,741	23,714
Hospitals Excluded: Critical Access Hospitals Hospitals in U.S. territories (American Samoa, Guam, Northern Mariana Islands, Puerto Rico, U.S. Virgin Islands)	 -1,291 0	 -1,302 0	 -1,330 0	 -1,342 -5	 -1,340 -5	 -6,605 -10
Study Population of non-CAH, non-federal, acute care hospitals	3,452	3,435	3,409	3,407	3,396	17,099
Merging with HIMSS Analytics data from the previous year	3,376	3,403	3,382	3,369	3,376	16,906
Merging with HCRIS data from the previous year	3,013	3,061	3,050	3,084	3,064	15,272
Merging with AHRF data from previous year	3,013	3,061	3,050	3,084	3,064	15,272
Keeping only non-missing observations for all study variables	2,965	3,011	3,007	3,041	3,024	15,048
Keeping only those hospitals that were observed across all 5 years of the study	2,738	2,738	2,738	2,738	2,738	**13,690**

Comparison of Study Population and Sample

The results of the comparison between the study population and the study sample are presented in Table 4. A pooled cross-sectional database of the dependent variable measures was constructed from 2009 to 2013 and a pooled cross-sectional database of the independent variables was constructed from 2008 to 2012 to compare the characteristics of the study population with the study sample. The observations for all variables were then averaged across the observed years for each unique hospital. For the dependent and the independent variables obtained from the HIMSS Analytics database, comparisons were made between the study sample and all non-CAH, non-federal, acute care hospitals in the study population in the HIMSS Analytics Database. Similarly, for the independent variables obtained from the HCRIS database, comparisons were made between the study sample and all the non-CAH, non-federal, acute care hospitals in the study population in the HCRIS database. T-tests and chi-square tests were used to compare the continuous and categorical variables respectively. The null hypothesis tested in this comparison was that the sample means or proportions represented by the study sample were equal to the true means or proportions of the study population. For all the dependent and independent variables, there were no statistically significant differences between the study population and study sample at $p<0.05$ level. Hence, the study sample was representative of the study population.

Table 4: Comparison of Non-CAH, Non-federal, Acute Care Hospitals in Study Population and Sample

Variables from HIMSS Analytics Database				
Variable	**Population (N=3,563) Mean (SD)**	**Sample (N=2,738) Mean (SD)**	**t-statistic**	**P-value**
Dependent Variables: 2009 to 2013				
GLOBAL_ADOPT	6.423 (1.836)	6.487 (2.029)	1.650	0.099
MU_MMT	0.386 (0.361)	0.395 (0.489)	0.963	0.336
CLOSEDLOOP	0.366 (0.380)	0.382 (0.486)	1.723	0.085
ORDER	1.312 (0.522)	1.327 (0.640)	1.226	0.220
TRANSCRIBE	1.408 (0.568)	1.427 (0.663)	1.499	0.134
DISPENSE	0.813 (0.620)	0.827 (0.622)	1.177	0.239
ADMINISTER	0.811 (0.625)	0.834 (0.745)	1.615	0.106
Independent Variables: 2008 to 2012				
SIZE	211.1 (169.3)	213.7 (177.8)	0.765	0.444
SYSTEM	0.628 (0.457)	0.613 (0.487)	-1.612	0.107
TEACH	0.073 (0.241)	0.081 (0.273)	1.533	0.125
Variables from HCRIS Database				
Variable	**Population (N=3,512) Mean (SD)**	**Sample (N=2,738) Mean (SD)**	**t-statistic**	**P-value**
Independent Variables: 2008 to 2012				
HHI	0.553 (0.353)	0.559 (0.357)	0.879	0.379
INCOME	49380.8(12894.2)	49516.9 (13297.5)	0.536	0.592
OPERATING_MARGIN	-0.019 (0.219)	-0.014 (0.146)	-1.792	0.073
PRIVATE_PAYER	0.447 (0.148)	0.443 (0.136)	-1.539	0.124
FOR_PROFIT	0.209 (0.425)	0.200 (0.400)	-1.777	0.239
NON_PROFIT	0.615 (0.482)	0.628 (0.483)	1.411	0.158
METRO_ADJ	0.152 (0.359)	0.160 (0.367)	1.14	0.254
RURAL	0.105 (0.307)	0.107 (0.310)	0.338	0.736

Sample Descriptive Characteristics

The descriptive statistics of the study sample, including the means and standard deviations or frequencies and proportions for the dependent and independent variables, are presented in Table 5. The distributions of all the variables were examined for skewness and kurtosis and log transformation was performed where appropriate. Two independent variables-hospital size (SIZE) and median household income (INCOME) were log transformed since the data distributions were skewed. The operating margin variable (OPERATING_MARGIN) showed extreme outliers. Hence, this variable was winsorized at the 1st and 99th percentile.

Winsorization is a well-accepted method to control for extreme outliers in financial data without completely removing the outlier from the analysis (Black, Jang, & Kim, 2006; Durnev & Kim, 2005). The winsorized operating margin variable was then used in further analyses. Means and standard deviations were examined for the continuous variables and frequencies and proportions were examined for the categorical variables for the pooled study sample (2009 to 2013 for the dependent variable and 2008 to 2012 for the independent variables).

As previously defined in Chapter 4, the variable of adoption of MMTs was measured through seven outcome measures:

1) Global adoption of MMTs (GLOBAL_ADOPT): a count of the total number of MMTs that were adopted by the hospital.
2) Adoption of MU MMT (MU_MMT): dichotomous variable representing whether or not the hospital adopted all three MU MMTs (CPOE, CDSS, eMAR).
3) Adoption of CLMM (CLOSEDLOOP): dichotomous variable representing whether the hospital adopted closed-loop medication administration at point of care or not.
4) Adoption of ordering technology (ORDER): a categorical variable representing the level of adoption of ordering technologies defined as low adoption (adoption of no technology), medium adoption (adoption of one technology) and high adoption (adoption of both technologies).
5) Adoption of transcribing technology (TRANSCRIBE): a categorical variable representing the level of adoption of transcribing technologies defined as low adoption (adoption of no technology), medium adoption (adoption of one technology) and high adoption (adoption of both technologies).
6) Adoption of dispensing technology (DISPENSE): a categorical variable representing the level of adoption of dispensing technologies defined as low adoption (adoption of less than three

technologies), medium adoption (adoption of three technologies) and high adoption (adoption of more than three technologies).

7) Adoption of administration technology (ADMINISTER): a categorical variable representing the level of adoption of administration technologies defined as low adoption (adoption of less than two technologies), medium adoption (adoption of two technologies) and high adoption (adoption of more than two technologies).

In the pooled five-year sample of hospitals, the mean number of MMTs adopted were 6.5. Further, 39.5% of the hospitals adopted all three MU MMTs and 38.2% of the hospitals adopted CLMM. For ordering technologies, 9.4% of the hospitals had low adoption, 48.4% had medium adoption and 42.2% had high adoption levels. For transcribing technologies, 9.7% of the hospitals had low adoption, 37.9% had medium adoption and 52.4% had high adoption levels. For dispensing technologies, 31.2% of the hospitals had low adoption, 58.3% had medium adoption and 12.2.6% had high adoption levels. For administration technologies, 37.5% of the hospitals had low adoption, 41.67% had medium adoption and 20.9% had high adoption levels. The mean value of HHI was 0.6. The mean value of INCOME was 49,516.8 and the mean value of log (INCOME) was 10.77. Further, 16.0% of the hospitals were located in metropolitan adjacent areas, 10.7% were located in rural areas and the remaining in metropolitan areas. The mean value of SIZE was 213.7 and the mean value of log (SIZE) was 5.0. The mean value of the operating margin was -0.01, while the average private payer mix was 44.3%. System members accounted for 61.3% and teaching hospitals accounted for 8.1% of the hospitals. Only 20.0% of the hospitals were for-profit, while 62.8% of the hospitals were non-profit hospitals and the remainder were public hospitals.

Table 5: Descriptive Statistics for Study Variables for all Years (n=13,690)

Variable	Definition	Frequency (%)	Mean (SD)	Min	Max
Dependent Variables: 2009 to 2013					
GLOBAL_ADOPT	Total number of MMTs adopted	-	6.487 (2.029)	0.000	12.000
MU_MMT	1=adopt all three MU MMTs; 0=otherwise	0=8,285 (60.52) 1=5,405 (39.48)	-	-	-
CLOSEDLOOP	1= adopted CLMM; 0 = otherwise	0=8,460 (61.80) 1=5,230 (38.20)	-	-	-
ORDER	0= low adoption; 1= medium adoption; 2=high adoption	0=1,292 (9.44) 1=6,623 (48.38) 2=5,775 (42.18)	-	-	-
TRANSCRIBE	0= low adoption; 1= medium adoption; 2=high adoption	0=1,330 (9.72) 1=5,182 (37.85) 2=7,178 (52.43)	-	-	-
DISPENSE	0= low adoption; 1= medium adoption; 2=high adoption	0=4,042 (31.23) 1=7,976 (58.26) 2=1,672 (12.21)	-	-	-
ADMINISTER	0= low adoption; 1= medium adoption; 2=high adoption	0=5,129 (37.47) 1=5,705 (41.67) 2=2,856 (20.86)	-	-	-
Independent Variables: 2008 to 2012					
Environmental Factors					
PRE_HITECH	1=Year 2009 or 2010; 0=Otherwise	0=8,214 (60.00) 1=5,476 (40.00)	-	-	-
POST_HITECH	1=Year 2012 or 2013; 0=Otherwise	0=8,214 (60.00) 1=5,476 (40.00)	-	-	-
HHI	Sum of Squared Market Shares of Inpatient Days	-	0.559 (0.357)	0.020	1.000
INCOME	Median Household Income of the County	-	49516.860 (13297.520)	20486.000	119525.000
LOG_INCOME	Ln(Median Household Income of the County)	-	10.777 (0.252)	9.927	11.691
METRO_ADJ	1=Metropolitan Adjacent County; 0=Otherwise	0=11,498 (83.99) 1=2,192 (16.01)	-	-	-

RURAL	1=Rural County; 0=Otherwise	0=12,220 (89.26) 1=1,470 (10.74)	-	-	-
Organizational Factors					
SIZE	Total Number of Beds Set Up and Staffed	-	213.729 (177.778)	4.000	1558.000
LOG_SIZE	log (Total Number of Beds Set Up and Staffed)	-	5.0337 (0.849)	1.386	7.351
SYSTEM	1=System Member; 0=Otherwise	0=5,298 (38.70) 1=8,392 (61.30)	-	-	-
OPERATING_MARGIN	(Operating Revenue-Operating Expenses)/Operating Revenue	-	-0.014 (0.146)	-0.748	0.307
PRIVATE_PAYER	Private Insurance Inpatient Days/Total Inpatient Days	-	0.443 (0.136)	0.002	0.991
FOR_PROFIT	1=For-Profit; 0=Otherwise	0=10,947 (79.96) 1=2,743 (20.04)	-	-	-
NON_PROFIT	1=Non-Profit; 0=Otherwise	0=5,097(37.23) 1=8,593 (62.77)	-	-	-
TEACH	1=Teaching Hospital; 0=Otherwise	0=12,583 (91.91) 1=1,107 (8.09)	-	-	-

Changes in the Dependent Variable Measures from the Pre-HITECH period to the Post-HITECH Period

The changes in the means and proportions for the dependent variable between the periods before the implementation of the HITECH Act (PRE_HITECH), during the HITECH Act implementation year and after the implementation of the HITECH Act (POST_HITECH) was examined. The PRE_HITECH value was obtained by averaging the observations for the year 2009 and 2010. The HITECH value was obtained from the observations of the year 2011. The POST_HITECH value was obtained by averaging the observations for the year 2012 and 2011. The percentage change was computed as [(POST_HITECH value-PRE_HITECH value)/(PRE_HITECH value)]*100. Between the pre-HITECH period and the post-HITECH period, the mean number of MMTs adopted increased significantly from 5.91 to 7.08 ($p<0.001$). The proportion of hospitals that adopted all three MU MMTs increased from 21.2% to 36.4% ($p<0.001$) and the proportion of hospitals that adopted CLMM increased from 22.7% to 34.1% ($p<0.001$). Also, the mean adoption level of ordering technologies increased from 1.09 to 1.25 ($p<0.001$), the mean adoption level of transcribing technologies increased from 1.32 to 1.40 ($p<0.001$), the mean adoption level of dispensing technologies increased from 0.73 to 0.89 ($p<0.001$) and the mean adoption level of administration technologies increased from 0.86 to 1.17 ($p<0.001$). A summary of the changes in the dependent variable measures between the pre-HITECH period and the post-HITECH period is presented in Table 6. Further, a graphical representation is presented in Figure 4. The graphical representation shows a steeper increase in all the measures of the dependent variable between the HITECH period and the post-HITECH period as compared to the increase from the pre-HITECH period to the HITECH period.

Table 6: Changes in the Dependent Variable Measures from the pre-HITECH period to the post-HITECH period

Dependent Variable Measures	PRE_ HITECH period (A)	HITECH period	POST_ HITECH period (B)	%Change [(B-A)/A] *100	P-value
GLOBAL_ADOPT	5.9129	6.4408	7.0849	19.8211	0.000***
MU_MMT	0.2160	0.3762	0.5829	169.8611	0.000***
CLOSEDLOOP	0.2274	0.3532	0.5511	142.3483	0.000***
ORDER	1.1041	1.3104	1.5594	41.2372	0.000***
TRANSCRIBE	1.3382	1.4229	1.5183	13.4584	0.000***
DISPENSE	0.7482	0.8119	0.9131	22.0396	0.000***
ADMINISTER	0.6563	0.8126	1.0222	55.7519	0.000***
*p<0.05; **p<0.01; ***p<0.001					

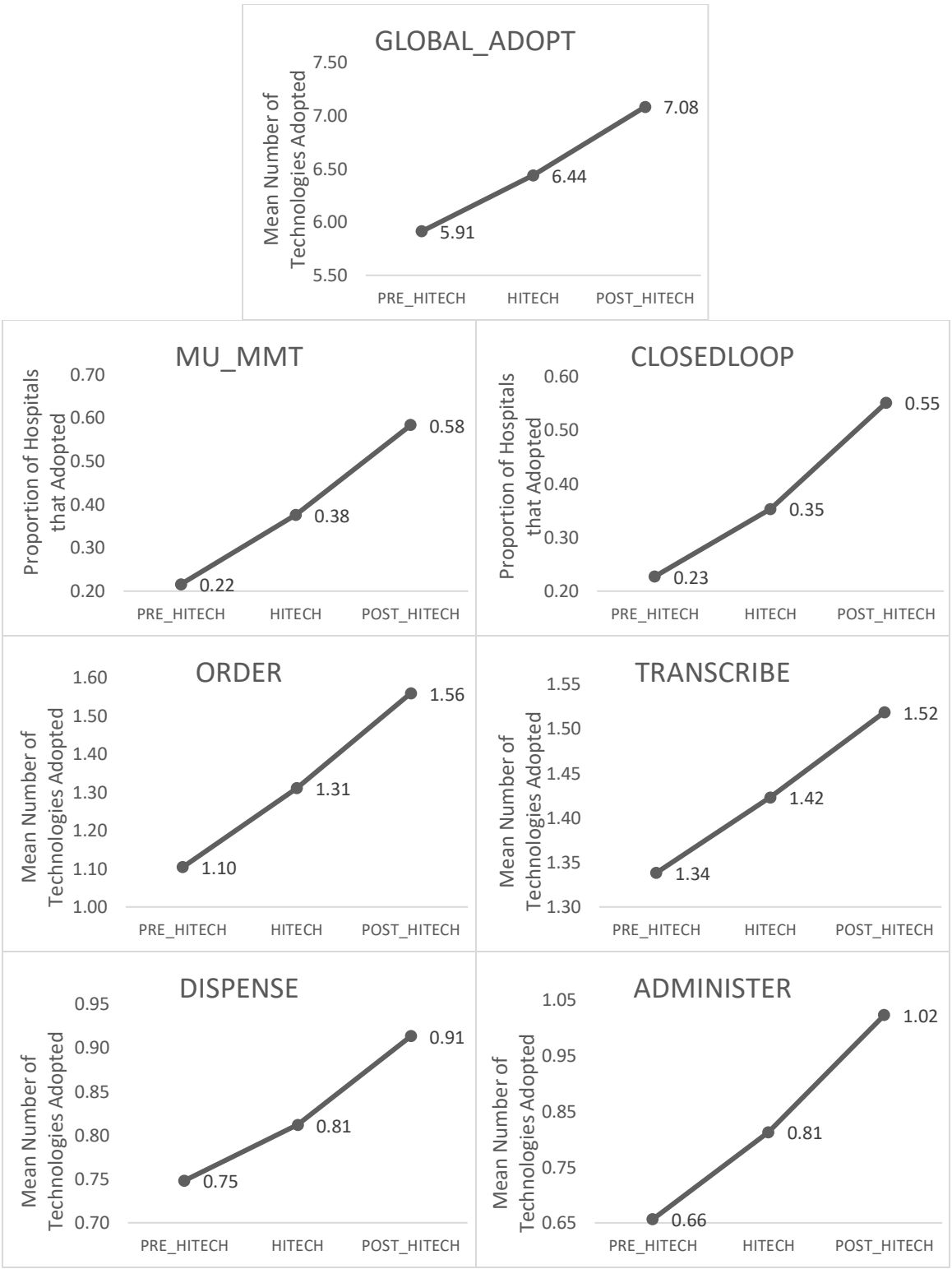

Figure 4: Changes in Dependent Variable Measures from Pre-HITECH period to Post-HITECH period.

PRE_HITECH: Average value of the observations for the year 2009 and 2010
HITECH: Value of the observations for the year 2011
POST_HITECH: Average value of the observations for the year 2012 and 2013

Correlation Analysis

In addition to the above descriptive analysis, a correlation analysis of the pooled five-year data was conducted to detect any multicollinearity between the independent variables and to evaluate which independent variables could be used in the multivariate models. Table 7 summarizes the results of the correlation analysis. The standard cut-off point ($r = 0.70$) was used. The correlation co-efficient of all paired variables was lower than 0.70, indicating the lack of multicollinearity in the data. Thus, all the independent variables were included in the multivariate regression models.

Table 7: Correlation Analysis for Pooled Analytic Sample (n=13,690)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. PRE_HITECH	1.000												
2. POST_HITECH	-0.667	1.000											
3. HHI	-0.003	0.003	1.000										
4. LOG_INCOME	0.020	0.007	-0.401	1.000									
5. METRO_ADJ	0.001	0.000	0.429	-0.335	1.000								
6. RURAL	0.000	0.000	0.361	-0.315	-0.151	1.000							
7. LOG_SIZE	0.003	-0.003	-0.495	0.244	-0.351	-0.286	1.000						
8. SYSTEM	-0.026	0.026	-0.250	0.112	-0.148	-0.157	0.185	1.000					
9. OPERATING_ MARGIN	0.016	-0.033	0.017	0.061	-0.053	-0.044	0.071	0.243	1.000				
10. PRIVATE_ PAYER	-0.067	0.081	-0.384	0.380	-0.272	-0.273	0.335	0.202	0.104	1.000			
11. FOR_PROFIT	-0.017	0.017	-0.037	-0.100	0.009	-0.013	-0.109	0.285	0.204	-0.062	1.000		
12. NON_PROFIT	0.010	-0.008	-0.105	0.207	-0.094	-0.090	0.196	0.026	0.056	0.145	-0.650	1.000	
13. TEACH	0.041	-0.030	-0.248	0.106	-0.128	-0.099	0.374	0.032	-0.103	0.202	-0.121	0.044	1.000

Multivariate Regression Analyses Results

Multivariate regression analyses were conducted using Stata/SE 14.2 and SAS 9.4 software (SAS Institute Inc., Cary, North Carolina; StataCorp LP., College Station, TX). The sample size was 13,690 hospital years, representing 2,738 unique hospitals over five years. The dataset was balanced panel i.e., all the hospitals were observed for the entire study period of five years. The panel data were then analyzed using panel data analytical models such as fixed effects, random effects and multi-level or mixed effects models. One outcome of interest (GLOBAL_ADOPT) was a count variable and hence a Poisson regression model was appropriate. Two measures of adoption of MMTs (CLOSEDLOOP and MU_MMT) were dichotomous variables and hence, logistic regression models were appropriate. For Poisson and logistic regression models, specification of fixed effects, random effects and mixed effects is possible. The remaining four outcomes of interest (ORDER, TRANSCRIBE, DISPENSE and ADMINISTER) were categorical variables with three levels. Hence, multinomial logistic regression models were appropriate. For the multinomial logistic regression models, fixed effects specification alone was not possible as its use is limited in practice due to unfeasible computations (Pforr, 2011). Further, the analytical dataset was multi-level in nature i.e., the dataset consisted of hospitals nested within counties, which were further nested within states and both organizational and count-level factors were used in the regression analyses. Hence given this multi-level nature of the dataset, a mixed effects model for the multinomial logistic regression was used.

Specification Tests of Consistency

Since for GLOBAL_ADOPT, CLOSEDLOOP and MU_MMT, fixed effects as well as random effects specification was possible; the Hausman specification test was used to decide between the fixed effects model and the random effects model. In all three cases, the Hausman specification test rejected the null hypothesis of no systematic differences between the fixed

effects and random effects co-efficient estimates (Table 8). Therefore, the Hausman Specification Test favored the fixed effects model. However, the fixed effects model drops all the time-invariant variables from the model. Since, some of the key independent variables in this study (for e.g. system membership, ownership status, etc.) were not expected to vary over time for a specific hospital, a fixed-effects model may not be appropriate to test the hypotheses for this study. Hence, multi-level or mixed-effects regression models would be more appropriate for these three outcomes of interest. This mixed effects approach allows modeling both the fixed effects as well as the random effects. Further, it is also appropriate for the multi-level nature of this dataset (i.e., facility and county-level factors). Also, a mixed-effects model was chosen for the remaining four outcomes of interest (ORDER, TRANSCRIBE, DISPENSE and ADMINISTER). Thus, a mixed-effects model was appropriate for all the seven dependent variables.

Different mixed effects models were examined such as models with hospital random intercept only, hospital and county-level random intercepts, hospital and state-level random intercepts and hospital, county and state-level random intercepts. The models with the lowest Akaike Information Criterion (AIC) values were chosen for each measure of the dependent variable and are presented in this section. Statistical significance was assessed at $p<0.05$ and $p<0.10$ was considered as marginally significant.

Table 8: Hausman Specification Test

Dependent Variable	χ^2	P-value
GLOBAL_ADOPT	106.21	<0.001
MU_MMT	88.58	<0.001
CLOSEDLOOP	91.17	<0.001

Model 1: Global Adoption of MMTs

Model 1 examined the impact of the HITECH Act on the adoption of the number of MMTs by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a Poisson regression model. For this variable, the model with the best AIC was the

mixed-effects model with random hospital, county and state-level intercepts. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals adopted 11% more MMTs in the post-HITECH period ($p<0.001$) and 8% less MMTs in the pre-HITECH period ($p<0.001$) as compared to the HITECH period. Contrary to expectation, hospitals with one unit higher HHI (i.e., lower competition) had adopted 1.04 more number of MMTs ($p<0.05$). Contrary to expectation, community wealth was not statistically significant in this model. As expected, larger hospitals adopted a higher number of MMTs ($p<0.001$). Contrary to what was expected, system membership was not statistically significant. As expected, hospitals with one unit higher operating margin adopted 1.13 more number of MMTs ($p<0.001$) and hospitals with one unit higher private payer mix adopted 1.35 more number of MMTs. Contrary to what was expected, for-profit hospitals adopted 11% lower MMTs as compared to public hospitals ($p<0.001$). The results from this model are presented in Table 9.

Table 9: Parameter Estimates: Global Adoption of MMTs

Correlate	Exp(β)	95% CI for Exp(β)		P-value
		Lower Limit	Upper Limit	
Environmental Factors				
PRE_HITECH vs. HITECH	0.918	0.901	0.935	0.000***
POST_HITECH vs. HITECH	1.096	1.077	1.116	0.000***
HHI	1.044	1.003	1.087	0.035*
LOG_INCOME	1.043	0.991	1.098	0.104
METRO_ADJ vs. METROPOLITAN	1.024	0.992	1.058	0.139
RURAL vs. METROPOLITAN	1.004	0.967	1.042	0.848
Organizational Factors				
LOG_SIZE	1.108	1.093	1.122	0.000***
SYSTEM	0.992	0.972	1.012	0.431
OPERATING_MARGIN	1.128	1.061	1.200	0.000***
PRIVATE_PAYER_MIX	1.353	1.245	1.470	0.000***
FOR_PROFIT vs. PUBLIC	0.888	0.859	0.917	0.000***
NON_PROFIT vs. PUBLIC	1.004	0.978	1.031	0.775
TEACH	1.027	0.994	1.061	0.111
Sample Size=13,690; Level 2 units=2,738; Level 3 units=1,447; Level 4 units=51				
Exp(β): Exponentiated co-efficient; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001				

Model 2: Adoption of MU MMTs

Model 2 examined the impact of the HITECH Act on adoption of all three MU MMTs (CPOE, CDSS and eMAR) by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a logistic regression model. For this variable, the mixed effects model with random hospital, county and state-level intercepts had the lowest AIC. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals were 6.94 times more likely to adopt all three MU MMTs in the post-HITECH period (OR: 6.939; $p<0.001$) and 0.16 times less likely to adopt all three MU MMTs in the pre-HITECH period (OR:0.158; $p<0.001$) as compared to the HITECH Act implementation period. Contrary to expectations, HHI (competition) was not statistically significant in this model. As expected, hospitals in counties with higher community wealth were more likely to adopt all three MU MMTs (OR: 2.680; $p<0.01$). As expected, larger hospitals were more likely to adopt all three MU MMTs (OR: 1.553; $p<0.001$). Contrary to what was predicted, operating margin was not statistically significant in this model. As expected, hospitals with one unit higher private payer mix were almost 42 times more likely to adopt all three MU MMTs (OR:42.094; $p<0.001$). Contrary to expectation, for-profit hospitals were less likely to adopt all three MU MMTs as compared to public hospitals (OR: 0.128; $p<0.001$). Among the control variables, teaching hospitals were almost three times more likely to adopt all three MU MMTs (OR: 3.002; $p<0.001$). The results from this model are presented in Table 10.

Table 10: Parameter Estimates: Adoption of Meaningful Use MMTs

Correlate	OR	95% CI for OR		P-value
		Lower Limit	Upper Limit	
Environmental Factors				
PRE_HITECH vs. HITECH	0.158	0.133	0.187	0.000***
POST_HITECH vs. HITECH	6.939	5.898	8.165	0.000***
HHI	1.262	0.711	2.240	0.427
LOG_INCOME	2.680	1.303	5.510	0.007**
METRO_ADJ vs. METROPOLITAN	1.139	0.710	1.828	0.588
RURAL vs. METROPOLITAN	1.387	0.798	2.411	0.246
Organizational Factors				
LOG_SIZE	1.553	1.283	1.879	0.000***
SYSTEM	0.806	0.616	1.053	0.114
OPERATING_MARGIN	0.562	0.272	1.161	0.120
PRIVATE_PAYER_MIX	42.094	14.728	120.307	0.000***
FOR_PROFIT vs. PUBLIC	0.128	0.081	0.202	0.000***
NON_PROFIT vs. PUBLIC	1.002	0.692	1.450	0.992
TEACH	3.002	1.949	4.622	0.000***
Sample Size=13,690; Level 2 units=2,738; Level 3 units=1,447; Level 4 units=51				
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001				

Model 3: Adoption of CLMM

Model 3 examined the impact of the HITECH Act on the adoption of CLMM by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a logistic regression model. For this variable, the mixed effects model with random hospital, county and state-level intercepts had the lowest AIC. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals were 12.71 times more likely to adopt CLMM in the post-HITECH period (OR: 12.714; $p<0.001$) and 0.16 times less likely to adopt CLMM in the pre-HITECH period (OR: 0.157; $p<0.001$) as compared to the HITECH Act implementation period. Contrary to expectations, HHI (competition) and community wealth were not statistically significant in this model. As expected, larger hospitals were more likely to adopt CLMM (OR: 1.924; $p<0.001$). Contrary to what was predicted, system members were 0.55 times less likely to adopt CLMM (OR: 0.553; $p<0.05$) as compared to non-system members. Hospitals with one unit higher operating margin were almost five times more likely to adopt CLMM (OR: 5.071; $p<0.01$) and hospitals with one unit higher

private payer mix were almost 20 times more likely to adopt CLMM (OR:20.003; p<0.001). Contrary to what was expected, for-profit hospital ownership was not statistically significant in this model. The results from this model are presented in Table 11.

Table 11: Parameter Estimates: Adoption of CLMM

Correlate	OR	95% CI for OR		P-value
		Lower Limit	Upper Limit	
Environmental Factors				
PRE_HITECH vs. HITECH	0.157	0.129	0.191	0.000***
POST_HITECH vs. HITECH	12.714	10.339	15.634	0.000***
HHI	0.764	0.318	1.837	0.548
LOG_INCOME	1.583	0.567	4.424	0.381
METRO_ADJ vs. METROPOLITAN	1.564	0.768	3.183	0.218
RURAL vs. METROPOLITAN	1.080	0.467	2.496	0.857
Organizational Factors				
LOG_SIZE	1.924	1.452	2.550	0.000***
SYSTEM	0.553	0.381	0.804	0.002**
OPERATING_MARGIN	5.071	1.959	13.122	0.001**
PRIVATE_PAYER_MIX	20.003	4.761	84.051	0.000***
FOR_PROFIT vs. PUBLIC	0.700	0.368	1.330	0.276
NON_PROFIT vs. PUBLIC	1.156	0.675	1.979	0.598
TEACH	0.658	0.339	1.277	0.216
Sample Size=13,690; Level 2 units=2,738; Level 3 units=1,447; Level 4 units=51				
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001				

Model 4: Adoption of Ordering Technologies

Model 4 examined the impact of the HITECH Act on the adoption levels of ordering technologies by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a multinomial logistic regression model. For this variable, the model with the best AIC was the mixed-effects model with random hospital-level intercepts. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant (p<0.001). In line with what was predicted, hospitals had 5.91 times higher odds to be medium adopters and 13.91 times higher odds to be high adopters in post-HITECH period (p<0.001) as compared to the HITECH period and 0.25 times lower odds of medium adoption level and 0.12 times lower odds of high adoption level in the pre-HITECH period (p<0.001) as compared to the HITECH period.

Contrary to expectations, hospitals with one unit higher HHI (i.e., lower competition) were significantly more likely to be medium-level adopters and high-level adopters ($p<0.01$). As expected, higher community wealth was significantly associated with increased likelihood of having medium adoption ($p<0.05$) and high adoption ($p<0.01$).

As predicted, larger hospital size was positively associated with the likelihood of medium adoption and high adoption ($p<0.001$) and system members were 1.60 times more likely to be medium adopters ($p<0.05$) as compared to non-system members, though system membership was not significantly associated with odds of high adoption. Contrary to expectation, higher operating margin was only marginally significantly associate ($p<0.10$) with medium-level and high-level adoption. Hospitals with one unit higher private payer mix had significantly higher odds of being medium-level adopters ($p<0.01$) as well as high-level adopters ($p<0.001$). Contrary to what was expected, for-profit hospitals was only marginally associated with the likelihood of high adoption and not significantly associated with the likelihood of medium adoption. Among the control variables, teaching hospitals were 3.22 times more likely to be high adopters (OR: 3.221; $p<0.001$). The results from the model are presented in Table 12.

Table 12: Parameter Estimates: Adoption of Ordering Technologies

Correlate	ORDER	OR	95% CI for OR		P-value
			Lower Limit	Upper Limit	
Environmental Factors	Ref=Low				
PRE_HITECH vs. HITECH	Medium	0.250	0.185	0.340	0.000***
	High	0.117	0.086	0.159	0.000***
POST_HITECH vs. HITECH	Medium	5.907	4.025	8.669	0.000***
	High	13.908	9.471	20.425	0.000***
HHI	Medium	3.540	1.604	7.811	0.002**
	High	3.541	1.596	7.855	0.002**
LOG_INCOME	Medium	3.349	1.236	9.072	0.017*
	High	4.474	1.643	12.188	0.003**
METRO_ADJ vs. METROPOLITAN	Medium	1.571	0.751	3.289	0.230
	High	1.570	0.746	3.305	0.235
RURAL vs. METROPOLITAN	Medium	1.074	0.455	2.536	0.871
	High	1.127	0.474	2.678	0.787
Organizational Factors					
LOG_SIZE	Medium	4.811	3.421	6.765	0.000***
	High	5.440	3.862	7.663	0.000***
SYSTEM	Medium	1.595	1.012	2.515	0.044*
	High	1.370	0.867	2.166	0.177
OPERATING_MARGIN	Medium	3.097	0.929	10.322	0.066Ψ
	High	3.050	0.906	10.267	0.072Ψ
PRIVATE_PAYER	Medium	11.663	2.262	60.123	0.003**
	High	49.962	9.586	260.391	0.000***
FOR_PROFIT vs. PUBLIC	Medium	1.657	0.797	3.448	0.176
	High	0.510	0.243	1.069	0.074Ψ
NON_PROFIT vs. PUBLIC	Medium	1.224	0.677	2.212	0.504
	High	1.320	0.728	2.393	0.361
TEACH	Medium	1.462	0.639	3.343	0.369
	High	3.221	1.408	7.365	0.006**
Sample Size=13,690; Level 2 units=2,738					
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001					

Model 5: Adoption of Transcribing Technologies

Model 5 examined the impact of the HITECH Act on the adoption levels of transcribing technologies by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a multinomial logistic regression model. For this variable, the model with the best AIC was the mixed-effects model with random hospital-level intercepts. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals had 1.51 times higher odds to be medium adopters and twice

the odds to be high adopters in post-HITECH period ($p<0.001$) as compared to the HITECH period and 0.71 times lower odds of high adoption level in the pre-HITECH period ($p<0.01$) as compared to the HITECH period. Contrary to expectations, hospitals with one unit higher HHI (i.e., lower competition) were significantly more likely to be medium-level adopters and high-level adopters ($p<0.001$). Contrary to what was predicted, higher community wealth was not statistically significantly associated with the likelihood of medium and high adoption.

As predicted, larger hospital size was positively associated with the likelihood of medium adoption and high adoption ($p<0.001$). Contrary to expectation, system membership was not statistically significant in this model. As expected, hospitals with one unit higher operating margin were almost three times more likely to be high adopters (OR: 3.274; $p<0.05$), although operating margin was not significantly associated with the likelihood of medium adoption. As expected, hospitals with one unit higher private payer mix had significantly higher odds of being medium-level and high-level adopters ($p<0.001$). Contrary to what was expected, for-profit hospitals were 0.29 times less likely to be medium adopters (OR: 0.290; $p<0.001$) and 0.18 times less likely to be high adopters (OR: 1.178; $p<0.001$) as compared to public hospitals. Among the control variables, hospitals located in rural areas had significantly higher odds of medium and high adoption ($p<0.01$) as compared to the hospitals located in metropolitan areas. The results from the model are presented in Table 13.

Table 13: Parameter Estimates: Adoption of Transcribing Technologies

Correlate	TRANSCRIBE	OR	95% CI for OR		P-value
			Lower Limit	Upper Limit	
Environmental Factors	Ref=Low				
PRE_HITECH vs. HITECH	Medium	0.985	0.786	1.234	0.895
	High	0.705	0.563	0.882	0.002**
POST_HITECH vs. HITECH	Medium	1.506	1.185	1.913	0.001**
	High	1.996	1.575	2.529	0.000***
HHI	Medium	3.351	1.719	6.530	0.000***
	High	7.792	4.005	15.159	0.000***
LOG_INCOME	Medium	0.916	0.404	2.076	0.834
	High	0.929	0.411	2.102	0.860
METRO_ADJ vs. METROPOLITAN	Medium	1.614	0.855	3.049	0.140
	High	1.648	0.874	3.107	0.122
RURAL vs. METROPOLITAN	Medium	2.782	1.325	5.844	0.007**
	High	2.745	1.309	5.756	0.008**
Organizational Factors					
LOG_SIZE	Medium	1.780	1.375	2.304	0.000***
	High	2.267	1.752	2.933	0.000***
SYSTEM	Medium	1.139	0.789	1.644	0.488
	High	1.049	0.727	1.513	0.798
OPERATING_MARGIN	Medium	1.285	0.504	3.272	0.600
	High	3.274	1.281	8.364	0.013*
PRIVATE_PAYER	Medium	11.997	3.341	43.071	0.000***
	High	37.444	10.453	134.127	0.000***
FOR_PROFIT vs. PUBLIC	Medium	0.290	0.161	0.520	0.000***
	High	0.178	0.099	0.320	0.000***
NON_PROFIT vs. PUBLIC	Medium	1.418	0.879	2.287	0.153
	High	1.725	1.070	2.779	0.025*
TEACH	Medium	1.328	0.712	2.477	0.373
	High	1.173	0.629	2.184	0.616
Sample Size=13,690; Level 2 units=2,738					
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001					

Model 6: Adoption of Dispensing Technologies

Model 6 examined the impact of the HITECH Act on the adoption levels of dispensing technologies by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a multinomial logistic regression model. For this variable, the model with the best AIC was the mixed-effects model with random hospital-level intercepts. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals had 2.88 times higher odds to be medium adopters and 2.75

times higher odds to be high adopters in post-HITECH period ($p<0.001$) as compared to the HITECH period and 0.55 times lower odds of medium adoption level and 0.58 times lower odds of high adoption level in the pre-HITECH period ($p<0.001$) as compared to the HITECH period. Contrary to expectations, hospitals with one unit higher HHI (i.e., lower competition) were significantly more likely to be medium-level adopters ($p<0.01$) and high-level adopters ($p<0.001$). Contrary to what was predicted, community wealth was not statistically significantly associated with likelihood of medium and high adoption.

As predicted, larger hospital size was positively associated with the likelihood of medium adoption and high adoption ($p<0.001$). Contrary to expectations, system membership was not statistically significantly associated with the likelihood of medium and high adoption. As expected, hospitals with one unit higher operating margin were almost five times more likely to be high adopters (OR:4.916; $p<0.001$), though operating margin was only marginally significant with medium-level adoption. As expected, hospitals with one unit higher private payer mix had significantly higher odds of being medium-level adopters as well as high-level adopters ($p<0.001$). Contrary to what was expected, for-profit hospitals were 0.50 times less likely to be high adopters ($p<0.01$) as compared to public hospitals, though for-profit status was not significantly associated with medium-level adoption. Among the control variables, hospitals located in metropolitan adjacent areas had significantly lower odds of high adoption ($p<0.05$) and those located in rural areas had significantly lower odds of high adoption ($p<0.01$) as compared to the hospitals located in metropolitan areas. The results from the model are presented in Table 14.

Table 14: Parameter Estimates: Adoption of Dispensing Technologies

Correlate	DISPENSE	OR	95% CI for OR		P-value
			Lower Limit	Upper Limit	
Environmental Factors	Ref=Low				
PRE_HITECH vs. HITECH	Medium	0.545	0.468	0.635	0.000***
	High	0.584	0.477	0.716	0.000***
POST_HITECH vs. HITECH	Medium	2.882	2.452	3.388	0.000***
	High	2.745	2.225	3.387	0.000***
HHI	Medium	2.386	1.419	4.013	0.001**
	High	4.104	2.366	7.120	0.000***
LOG_INCOME	Medium	0.603	0.319	1.141	0.120
	High	0.568	0.288	1.117	0.101
METRO_ADJ vs. METROPOLITAN	Medium	0.867	0.533	1.410	0.566
	High	0.510	0.294	0.885	0.017*
RURAL vs. METROPOLITAN	Medium	0.700	0.400	1.224	0.211
	High	0.342	0.180	0.652	0.001**
Organizational Factors					
LOG_SIZE	Medium	3.048	2.489	3.732	0.000***
	High	11.955	9.546	14.973	0.000***
SYSTEM	Medium	1.230	0.928	1.629	0.150
	High	0.809	0.598	1.095	0.170
OPERATING_MARGIN	Medium	1.906	0.936	3.882	0.075
	High	4.916	2.173	11.122	0.000***
PRIVATE_PAYER	Medium	20.061	7.673	52.449	0.000***
	High	73.289	25.238	212.825	0.000***
FOR_PROFIT vs. PUBLIC	Medium	0.875	0.555	1.379	0.565
	High	0.503	0.305	0.830	0.007**
NON_PROFIT vs. PUBLIC	Medium	0.953	0.656	1.385	0.802
	High	0.769	0.517	1.144	0.195
TEACH	Medium	1.757	1.075	2.872	0.025*
	High	1.661	1.003	2.750	0.048*
Sample Size=13,690; Level 2 units=2,738					
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001					

Model 7: Adoption of Administration Technologies

Model 7 examined the impact of the HITECH Act on the adoption levels of administration technologies by U.S. acute care hospitals and the organizational and environmental correlates of this adoption using a multinomial logistic regression model. For this variable, the model with the best AIC was the mixed-effects model with random hospital-level intercepts. The key policy variables of PRE_HITECH and POST_HITECH were statistically significant ($p<0.001$). In line with what was predicted, hospitals had almost four times higher

odds to be medium adopters and five times higher odds to be high adopters in post-HITECH period ($p<0.001$) as compared to the HITECH period and 0.44 times lower odds of medium adoption level and 0.30 times lower odds of high adoption level in the pre-HITECH period ($p<0.001$) as compared to the HITECH period. Contrary to expectations, hospitals with one unit higher HHI (i.e., lower competition) were significantly more likely to be medium-level adopters ($p<0.01$) and high-level adopters ($p<0.05$). Contrary to what was expected, higher community wealth was not statistically significantly associated with likelihood of medium and high adoption.

As predicted, larger hospital size was positively associated with the likelihood of medium adoption and high adoption ($p<0.001$). Contrary to what was predicted, system membership was not statistically significantly associated with the likelihood of medium and high adoption. As expected, higher operating margin was only significantly associated with the likelihood high adoption ($p<0.01$), though it was not statistically significantly associated with likelihood of medium adoption. As expected, hospitals with one unit higher private payer mix had significantly higher odds of being medium-level adopters as well as high-level adopters ($p<0.001$). Contrary to what was expected, for-profit hospitals were 0.55 times less likely to be high adopters ($p<0.001$) as compared to public hospitals, though for-profit status was not significantly associated with medium-level adoption. The results from the model are presented in Table 15.

Table 15: Parameter Estimates: Adoption of Administration Technologies

Correlate	ADMINISTER	OR	95% CI for OR		P-value
			Lower Limit	Upper Limit	
Environmental Factors	Ref=Low				
PRE_HITECH vs. HITECH	Medium	0.436	0.370	0.514	0.000***
	High	0.299	0.249	0.359	0.000***
POST_HITECH vs. HITECH	Medium	4.279	3.593	5.096	0.000***
	High	5.284	4.381	6.374	0.000***
HHI	Medium	2.585	1.311	5.097	0.006**
	High	2.066	1.039	4.109	0.039*
LOG_INCOME	Medium	1.694	0.752	3.817	0.204
	High	1.843	0.809	4.198	0.146
METRO_ADJ vs. METROPOLITAN	Medium	0.991	0.522	1.882	0.978
	High	0.981	0.512	1.881	0.954
RURAL vs. METROPOLITAN	Medium	0.781	0.377	1.618	0.506
	High	0.814	0.389	1.706	0.586
Organizational Factors					
LOG_SIZE	Medium	2.598	2.003	3.371	0.000***
	High	3.179	2.441	4.139	0.000***
SYSTEM	Medium	1.102	0.790	1.538	0.568
	High	0.827	0.589	1.161	0.273
OPERATING_MARGIN	Medium	1.808	0.810	4.033	0.148
	High	3.520	1.524	8.131	0.003**
PRIVATE_PAYER	Medium	31.909	10.012	101.700	0.000***
	High	32.209	9.844	105.381	0.000***
FOR_PROFIT vs. PUBLIC	Medium	0.792	0.444	1.414	0.431
	High	0.550	0.304	0.994	0.048*
NON_PROFIT vs. PUBLIC	Medium	0.815	0.510	1.300	0.390
	High	0.930	0.578	1.495	0.763
TEACH	Medium	0.660	0.369	1.181	0.162
	High	0.626	0.347	1.130	0.120
Sample Size=13,690; Level 2 units=2,738					
OR: Odds Ratio; Ψp<0.10; *p<0.05; **p<0.01; ***p<0.001					

Sensitivity Analysis

A sensitivity analysis using a Tobit regression model was conducted for Model 1, which examined the GLOBAL_ADOPT variable using a mixed-effects model with Poisson distribution and random hospital, county and state-level intercepts. Since this variable had an upper limit of 12 technologies that could be adopted by the hospital, a Tobit model would also be appropriate. The results from the Tobit model were consistent with those obtained from Model 1.

Summary of Chapter

This chapter presented the results of the descriptive and multivariate regression analyses. The study sample was not significantly different from the study population. Changes in the dependent variable measures before and after the implementation of the HITECH Act in 2011, revealed significant increases in all the measures with a steeper increase between the post-HITECH period and the HITECH period as compared to the increase between the HITECH period and the pre-HITECH period.

The multivariate analyses found that the key policy variable of the HITECH Act period was significantly associated with all seven dependent variables, with significantly higher adoption of MMTs in the post-HITECH Act period and lower adoption of MMTs in the pre-HITECH Act period, as compared to the HITECH Act period. Further, competition, hospital size, operating margin, private payer mix and ownership control were significantly associated with the global adoption of MMTs. Community wealth, hospital size, private payer mix, ownership control and teaching status were significantly associated with the adoption of MU MMTs. Competition, community wealth, geographic location, hospital size, system membership, private payer mix, ownership control and teaching status were significantly associated with the adoption levels of ordering technologies. Competition, geographic location hospital size, operating margin, private payer mix and ownership control were significantly associated with the adoption levels of transcribing technologies. Competition, geographic location, hospital size, system membership, private payer mix, ownership control and teaching status were significantly associated with the adoption levels of dispensing technologies. Competition, geographic location, hospital size, system membership and ownership control were significantly associated with the adoption levels of administration technologies.

In the final Chapter 6, a summary of the findings from the descriptive statistics and hypotheses testing through the multivariate analyses are presented. The chapter also provides the

interpretation of the results and a discussion of the implications of this study for future research, policy and practice. The chapter concludes with a discussion of the limitations of this study and opportunities for future research.

CHAPTER SIX: DISCUSSION

Introduction

The aim of this study was to examine the impact of the implementation of the HITECH Act on the adoption of MMTs by U.S. acute care hospitals as well as to assess the environmental and organizational correlates of the adoption of MMTs by U.S. acute care hospitals. Two research questions were posed in this study:

1) How did the implementation of the HITECH Act affect the adoption of MMTs in U.S. acute care hospitals?
2) What are the organizational and environmental factors that are associated with the adoption of MMTs in U.S. acute care hospitals?

Specifically, this study examined MMTs through their functional uses in the four steps of the medication management process: ordering, transcribing, dispensing and administration, adoption of CLMM; as well as through the global adoption of MMTs (total number of MMTs adopted) and adoption of MU MMTs (CDSS, CPOE and eMAR). This study derived its conceptual framework from the resource dependence theory (RDT) and the central empirical hypotheses of this study were: 1) After the implementation of the HITECH Act, U.S. acute care hospitals will be more likely to adopt MMTs; and 2) organizational factors and environmental factors will be associated with the adoption of MMTs by U.S. acute care hospitals. The organizational factors examined in this study were organizational size, system membership, financial resources, private payer mix and ownership control. The environmental factors that were examined were the degree of competition and community wealth in the hospital market. The study also included an organizational control variable of teaching status and an environmental control variable of the geographic location of the hospital.

Specific hypotheses were based upon the three key tenets of the RDT- uncertainty, munificence and interdependence. It was proposed that the implementation of the HITECH Act would bring about adoption and meaningful use of health IT. Thus, it was hypothesized that hospitals would be more likely to adopt MMTs in the period after the implementation of the HITECH Act. The basic MMTs that were required to be adopted by the HITECH Act were CPOE, CDSS and eMAR. Hence, hospitals would be more likely to adopt these three MMTs together in the period after the implementation of the HITECH Act. This policy effect was considered to create an uncertainty in the environment, leading to the hospitals to comply with the objectives of the policy to ensure survival. Further, it was also proposed that market competition, representing uncertainty; community wealth, hospital size, system membership and financial performance, representing munificence; and dependence on private insurance payers and shareholders, representing interdependence would be positively associated with adoption of MMTs. More specifically, being larger in size; being a system member; having financial resources; being a for-profit hospital; having a higher private payer mix; and operating in areas with higher competition and higher degree of community wealth would be positively associated with adoption of MMTs.

To test these hypotheses, data were drawn from three secondary administrative data sources: HIMSS Analytics Database, obtained from The Dorenfest Institute for H.I.T. Research and Education, HIMSS Foundation; HCRIS database, obtained from the CMS; and the county-level data from AHRF. The independent variables in the study were lagged by one year i.e., they were assessed for 2008 to 2012, while the dependent variable measures were assessed from 2009 to 2013. Only non-CAH, non-federal, acute care hospitals operating in the 50 U.S. States and the District of Columbia reporting to the HIMSS Analytics Database were included in the study population. After merging all three datasets, keeping only those observations with non-missing data for all study variables and keeping only those hospitals that were observed for all five years

of the study, the final sample size used in the empirical analyses was 13,690 for the years 2009 to 2013 consisting of balanced panel dataset of 2,738 unique hospitals. The ensuing paragraphs in this chapter summarize the findings from the descriptive and multivariate analyses, interpret these findings and discuss the implications of the study with respect to theory-based research, methodology, policy and practice. The limitations and future research directions are also described.

Summary and Interpretation of Descriptive Analyses

Descriptive analyses of the study variables were conducted using frequencies, proportions, means and standard deviations as appropriate and a correlation analysis was conducted. Correlation analysis revealed no issue of multicollinearity between the independent variables in this study. 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. Changes in the dependent variable measures before and after the implementation of the HITECH Act were examined. As expected, statistically significant increases were observed in all seven dependent variable measures after the implementation of the HITECH Act (post-HITECH) as compared to before (pre-HITECH). Interestingly, a graphical representation of the changes in the dependent variable measures with respect to HITECH Act implementation time period revealed a steeper increase in all dependent variable mneasures between the post-HITECH period and the HITECH period as compared to the increase from the pre-HITECH period to the HITECH period. This suggests that the adoption rate of MMTs was greater after the implementation of the HITECH Act, as compared to before the implementation.

Summary and Interpretation of Hypotheses Testing

The ensuing paragraphs discuss the interpretations of the hypotheses that were proposed in Chapter 3 based on the results of the empirical analyses presented in Chapter 5. The key outcome of interest of adoption of MMTs was operationalized through seven different measures:

(1) the global adoption of MMTs (GLOBAL_ADOPT), (2) adoption of MU MMTs (MU_MMT), (3) adoption of CLMM (CLOSEDLOOP), (4) adoption of ordering technologies (ORDER), (5) adoption of transcribing technologies (TRANSCRIBE), (6) adoption of dispensing technologies (DISPENSE) and (7) adoption of administration technologies (ADMINISTER). The following discussion will elaborate the findings based on these seven measures of adoption of MMTs.

H1: Hospitals will be more likely to adopt MMTs in the period after the implementation of the HITECH Act, all things being equal.

Hypothesis 1 proposed that hospitals will be more likely to adopt MMTs in the post-HITECH implementation period as compared to before the implementation of the Act. The findings of this study support this hypothesis through all the measures of the dependent variable examined in this study (GLOBAL_ADOPT, CLOSEDLOOP, MU_MMT, ORDER, TRANSCRIBE, DISPENSE and ADMINISTER) at the $p<0.05$ level. The coefficient estimates for the post-HITECH Act implementation variable (POST_HITECH) were positive and significant and the coefficient estimates for the pre-HITECH Act implementation variable (PRE_HITECH) were negative and significant at the $p<0.05$ level for all models. In the post-HITECH period, hospitals were significantly more likely to adopt MMTs and in the pre-HITECH period, hospitals were significantly less likely to adopt MMTs. In the post-HITECH Act period, financial incentives were offered by CMS to comply with the MU Stage 1 objectives while those who did not comply with the objectives would be penalized (Centers for Medicare and Medicaid Services, 2016d). The objective of the HITECH Act was to improve the quality of care through the use of technology (Centers for Medicare and Medicaid Services, 2016a). This policy enactment, which established financial incentives and penalties created an uncertain environment for the hospitals. In such an uncertain environment, hospitals may strategize to gain critical financial resources and ensure survival (Alexander & Morrisey, 1989; Apenteng et al., 2015; Banaszak-Holl et al., 1996; Kazley & Ozcan, 2007; Nayar, 2008). Thus, hospitals may have

adopted MMTs as a strategic decision to maintain the inflow of resources in an uncertain environment. Table 16 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 1.

Table 16: Confirmation of Hypothesis 1 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Positive	<0.001	Yes
Model 2: Adoption of MU MMTs		Positive	Positive	<0.001	Yes
Model 3: Adoption of CLMM		Positive	Positive	<0.001	Yes
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Positive	0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes

H2: Hospitals located in markets with higher competition will be more likely to adopt MMTs, all things being equal.

Hypothesis 2 proposed that competition in the hospital market would be positively associated with the adoption of MMTs. The findings of this study do not support this hypothesis for any of the seven outcome measures of interest. Competition was measured through HHI, which ranges from a scale of 0 to 1, with 0 capturing perfect competition and 1 capturing perfect monopoly. Hence, lower HHI implied higher competition. This study found a positive and significant association between HHI and GLOBAL_ADOPT and medium- and high-level adoption of ORDER, TRANSCRIBE, DISPENSE and ADMINISTER and no significant association between HHI and CLOSEDLOOP and MU_MMT. The positive association indicates that those hospitals that were located in less competitive markets were more likely to adopt MMTs.

This may be due to the reason that hospitals that were adopting MMTs could be doing so based on criteria other than competition. Further, MMTs are expensive which requires higher capital with uncertainties on the return on investments (Classen & Brown, 2013). In competitive environments, there is a limited pool of resources that the organizations share (Scott & Davis, 2003). To secure these resources, hospitals in a market with higher competition could be prioritizing other strategies such as advertising to attract patients, which could ensure their survival rather than the adoption of expensive technology with uncertain immediate returns. Although HHI was not significant with CLOSEDLOOP and MU_MMT, the direction of the association remained the same. The non-significant results indicate that hospitals may be prioritizing certain other strategies to ensure their survival. Table 17 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 2.

Table 17: Confirmation of Hypothesis 2 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Negative	0.035	No
Model 2: Adoption of MU MMTs		Positive	Negative	0.427	No
Model 3: Adoption of CLMM		Positive	Positive	0.548	No
Model 4: Adoption of Ordering Technologies	Medium	Positive	Negative	0.002	No
	High	Positive	Negative	0.002	No
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Negative	<0.001	No
	High	Positive	Negative	<0.001	No
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Negative	0.001	No
	High	Positive	Negative	<0.001	No
Model 7: Adoption of Administration Technologies	Medium	Positive	Negative	0.006	No
	High	Positive	Negative	0.039	No

H3: Hospitals located in markets with higher community wealth will be more likely to adopt MMTs, all things being equal.

Hypothesis 3 proposed that higher degree of community wealth would be positively associated with the adoption of MMTs. This study found mixed evidence to support this hypothesis. Two of the seven outcome measures of interest: MU_MMT and medium and high-

level of ORDER supported this hypothesis. Community wealth in the hospital market was measured through the median household income in the county that the hospital was located in (INCOME) and the coefficient estimates for the INCOME variable were positive and significant at the $p<0.05$ level for MU_MMT and medium and high-level adoption of ORDER. However, community wealth was not significantly associated with the remaining measures of the dependent variable at $p<0.05$ level.

Higher income in the county signifies a higher-paying patient base for the hospital and thus, the hospitals located in areas with higher income have access to affluent patient resources. These hospitals are assured of having access to these affluent resources in the long term. MU MMTs included CPOE, CDSS and eMAR, while ordering technologies included CPOE and CDSS. CPOE, CDSS and eMAR are technologies that are difficult to implement and require a longer implementation time. Hence, these hospitals that are assured of resources through their affluent environment may risk adopting these longer term implementation projects and hence could be more likely to adopt these technologies.

Table 18: Confirmation of Hypothesis 3 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Positive	0.104	No
Model 2: Adoption of MU MMTs		Positive	Positive	0.007	Yes
Model 3: Adoption of CLMM		Positive	Positive	0.381	No
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	0.017	Yes
	High	Positive	Positive	0.003	Yes
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Negative	0.834	No
	High	Positive	Negative	0.860	No
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Negative	0.120	No
	High	Positive	Negative	0.101	No
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	0.204	No
	High	Positive	Positive	0.146	No

H4: Larger hospitals will be more likely to adopt MMTs, all things being equal.

Hypothesis 4 proposed that organizational size was positively associated with the adoption of MMTs. This study found evidence to support this hypothesis through all the seven dependent variables. Larger hospital size was positively and significantly associated with all seven models at the $p<0.05$ level. Larger hospitals have access to more internal resources and can also control vital resources in the environment, thereby providing them with more resources to invest into new technologies (Kazley & Ozcan, 2007). The finding of this study resonates with previous organizational literature that also showed that larger organizations were more likely to adopt new technologies (Kazley & Ozcan, 2007; Kimberly & Evanisko, 1981). Table 19 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 4.

Table 19: Confirmation of Hypothesis 4 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Positive	<0.001	Yes
Model 2: Adoption of MU MMTs		Positive	Positive	<0.001	Yes
Model 3: Adoption of CLMM		Positive	Positive	<0.001	Yes
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes

H5: Hospitals that are part of a multi-hospital system will be more likely to adopt MMTs, all things being equal.

Hypothesis 5 proposed that system membership was positively associated with the adoption of MMTs. It was proposed that since system members have access to a larger pool of resources they would have the ability to adopt new technologies. The association between system membership and the dependent variable varied for the seven outcomes of interest. System

membership was negatively and significantly associated with CLOSEDLOOP, positively and significantly associated with medium-level adoption of ORDER, DISPENSE and ADMINISTER and not significantly associated with GLOBAL_ADOPT and TRANSCRIBE at the $p<0.05$ level. System membership was negatively and marginally significantly associated with the adoption of MU MMTs ($p<0.10$).

These findings indicated that system members were significantly less likely to adopt CLMM. A possible explanation for this could be that even though system members have access to resources through its member hospitals, they are also barriers when implementing major changes due to the difficulties in implementing changes across an entire system. CLMM is complex and involves high levels of coordination between different aspects of the medication management process and the different departments of the hospital engaged in this process (Bowles, 2012). Hence, system members may face barriers in implementing this complex system throughout their network. The significant association between system membership and medium-level adoption of ORDER but no association with the high-level adoption further emphasizes on the barriers faced by system members to achieve complete adoption owing to their complex network structure. Table 20 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 5.

Table 20: Confirmation of Hypothesis 5 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Negative	0.431	No
Model 2: Adoption of MU MMTs		Positive	Negative	0.114	No
Model 3: Adoption of CLMM		Positive	Negative	0.002	No
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	0.044	Yes
	High	Positive	Positive	0.177	No
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Positive	0.488	No
	High	Positive	Positive	0.798	No
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Positive	0.150	No
	High	Positive	Negative	0.170	No
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	0.568	No
	High	Positive	Negative	0.273	No

H6: Hospitals with greater financial resources will be more likely to adopt MMTs, all things being equal.

Hypothesis 6 proposed that having higher financial resources would be positively associated with the adoption of MMTs. This study found evidence to support this hypothesis through five out of the seven outcomes of interest. Availability of financial resources was measured by the operating margin of the hospital. There was positive and significant association between operating margin and GLOBAL_ADOPT, CLOSEDLOOP and high-level adoption of TRANSCRIBE, DISPENSE and ADMINISTER at the $p<0.05$ level. This indicates that hospitals with higher operating margin have the capital to invest in expensive new technology and hence may be more capable of adopting these MMTs.

There was no significant association between operating margin and MU_MMT, medium and high adoption of ORDER and medium-level adoption of TRANSCRIBE, DISPENSE and ADMINISTER. Adoption of all MMTs and adoption of CLMM is expensive and thus, higher financial resources are needed for their adoption. It is also interesting to note that operating margin was not significant for medium-level adoption of TRANSCRIBE, DISPENSE and ADMINISTER and was significant for their high-level adoption. This could be due to the fact

that MMTs are expensive (Classen & Brown, 2013) and thus, achieving a high-level adoption requires higher investment of capital. The non-significant association between operating margin and adoption of MU MMTs and ordering technologies resonates well with the findings of hypothesis 3. As described earlier in context of hypothesis 3, MU MMTs (CPOE, CDSS and eMAR) and ordering technologies (CPOE and CDSS) are difficult to implemenet and their implementation also takes a longer time than the transcribing, dispensing and administration technologies. Thus, hospitals that already have the financial resources may start out by adopting the technologies that are easier to implement and undertake longer term implementation projects later. Table 21 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 6.

Table 21: Confirmation of Hypothesis 6 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Positive	<0.001	Yes
Model 2: Adoption of MU MMTs		Positive	Negative	0.120	No
Model 3: Adoption of CLMM		Positive	Positive	0.001	Yes
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	0.066	No
	High	Positive	Positive	0.077	No
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Positive	0.600	No
	High	Positive	Positive	0.013	Yes
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Positive	0.075	No
	High	Positive	Positive	<0.001	Yes
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	0.148	No
	High	Positive	Positive	0.003	Yes

H7: Hospitals with a higher private payer mix will be more likely to adopt MMTs, all things being equal.

Hypothesis 7 proposed that having higher proportions of patients with private insurance was positively associated with adoption of MMTs. This study found evidence to support this hypothesis through all the seven measures of adoption of MMTs. Private payer mix was positively and significantly associated with GLOBAL_ADOPT, CLOSEDLOOP, MU_MMT and

medium and high adoption levels of ORDER, TRANSCRIBE, DISPENSE and ADMINISTER at the $p<0.05$ level.

This may be due to the reason that public payers such as Medicare and Medicaid reimburse hospitals at lower prices than the cost of providing services (Zinn et al., 1997), while the private insurance payers are more munificent payers for the hospitals. Hospitals with higher private payer mix are more dependent on the private payers and would be more likely to adopt new technologies that improve the quality of care provided to maintain this dependence and continue to attract these patients with private insurance. Table 22 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 7.

Table 22: Confirmation of Hypothesis 7 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Positive	<0.001	Yes
Model 2: Adoption of MU MMTs		Positive	Positive	<0.001	Yes
Model 3: Adoption of CLMM		Positive	Positive	<0.001	Yes
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	0.003	Yes
	High	Positive	Positive	<0.001	Yes
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes
Model 7: Adoption of Administration Technologies	Medium	Positive	Positive	<0.001	Yes
	High	Positive	Positive	<0.001	Yes

H8: For-profit hospitals will be more likely to adopt MMTs as compared to public hospitals, all things being equal.

Hypothesis 8 proposed that the for-profit status of the hospital was positively associated with the adoption of MMTs. This study did not find evidence for this hypothesis through any of the seven outcomes of interest. In fact, for-profit hospital status was negatively and significantly associated with GLOBAL_ADOPT, MU_MMT and high-level adoption of TRANSCRIBE, DISPENSE and ADMINISTER at the $p<0.05$ level. There was no significant association between

for-profit status and CLOSEDLOOP medium and high level adoption of ORDER and medium level adoption of TRANSCRIBE, DISPENSE and ADMINISTER. This indicates that for-profit hospitals were less likely to adopt most MMTs as compared to public hospitals.

This finding is consistent with previous work on the adoption of different MMTs (Abraham, McCullough, Parente, & Gaynor, 2011; Cutler et al., 2005; Furukawa et al., 2008). Cutler et al. (2005) reported that for-profit hospitals were less likely to adopt EMRs (Cutler et al., 2005) and Furukawa et al. (2008) reported a similar finding for EMR and CPOE (Furukawa et al., 2008). These findings were also consistent with the work done by Abraham et al. (2011), which reported that for-profit hospitals were less likely to adopt clinical IT such as EMR, CPOE, picture archiving communications systems (PACS), eMAR and nurse charts (Abraham et al., 2011). This negative association may be due to the resistance for for-profit hospitals to invest into expensive technologies (Abraham et al., 2011). Additionally, public hospitals could have more to gain from the benefits of MMTs as they have sicker patients and could benefit from the improvement in the outcomes through improvement in patient safety (Cutler et al., 2005). Moreover, with the political interest in patient safety and adoption of MMTs, leaders of public hospitals could be more willing to invest into them as compared to for-profit hospitals (Cutler et al., 2005). Although the association between for-profit status and adoption of CLMM was not significant at the $p<0.05$ level, the direction of the coefficient was consistent with the other models and was also marginally significant. Table 23 summarizes the results of the hypothesis testing and direction of coefficients for hypothesis 8.

Table 23: Confirmation of Hypothesis 8 and Direction of Coefficients

Model	Adoption Level	Expected Sign of Coefficient	Observed Sign of Coefficient	P-value	Supported at p<0.05
Model 1: Global Adoption of MMTs		Positive	Negative	<0.001	No
Model 2: Adoption of MU MMTs		Positive	Negative	<0.001	No
Model 3: Adoption of CLMM		Positive	Negative	0.276	No
Model 4: Adoption of Ordering Technologies	Medium	Positive	Positive	0.176	No
	High	Positive	Negative	0.074	No
Model 5: Adoption of Transcribing Technologies	Medium	Positive	Negative	<0.001	No
	High	Positive	Negative	<0.001	No
Model 6: Adoption of Dispensing Technologies	Medium	Positive	Negative	0.565	No
	High	Positive	Negative	0.007	No
Model 7: Adoption of Administration Technologies	Medium	Positive	Negative	0.431	No
	High	Positive	Negative	0.048	No

Implications for Theory-based Research

This study adds to the growing body of literature using organizational theory to explain the behavior of health care organizations. This is the only study of its kind to be using an organizational theory like RDT to explain the adoption of technologies specifically used for the automation of the medication management process while examining technologies for their specific functionality in the medication management process. This study provides empirical support for RDT in explaining the organizational and environmental correlates of innovation adoption.

With respect to the global adoption of MMTs and adoption of CLMM, it was found that the policy effect of the implementation of the HITECH Act, which represents uncertainty and the organizational characteristics of size and operating margin, which represent munificence and the organizational characteristic of private payer mix, which represents interdependence were important predictors. With respect to the adoption of MU MMTs and ordering technology, it was found that the policy effect of the implementation of the HITECH Act, which represents uncertainty and the environmental characteristic of community wealth and the organizational

characteristic of size, which represent munificence and the organizational characteristic of private payer mix, which represent interdependence were important predictors. With respect to high-level adoption of transcribing, dispensing and administration technology, it was found that the policy effect of the implementation of the HITECH Act, which represents uncertainty, the organizational characteristic of size, which represents munificence and the organizational characteristic of private payer mix, which represents interdependence were important predictors.

Thus, the factors associated with the adoption of MMTs depended on the type of technology considered. Hospitals do not adopt all MMTs, but are strategically choosing which type of MMT to be adopted depending on its organizational and environmental characteristics. This provided further evidence to the use of a resource dependence perspective as adoption of types of MMTs were strategic decisions of the hospitals.

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 of technologies by U.S. acute care hospitals. Most of the previous studies have used cross-sectional analyses when examining the factors related to the adoption of technology. The use of panel data and the panel data analyses methods in this study provide an improvement over the previously used methodologies. Especially, the use of a mixed-effects model allows for both fixed effects and random effects specification. Further, this model is also appropriate for the multi-level nature of the dataset.

Implications for Policy and Practice

Given the public health burden of medication errors and ADEs as described in Chapter 2, an increased emphasis has been put on the use of technologies by organizations such as Leapfrog, the IOM, the AHRQ, as well as through the HITECH Act to reduce these errors and improve the quality of care. This forms the core of the policy recommendations that have been put forth in the HITECH Act. The results of this study are likely to be of interest to policymakers, especially with

the uncertainties around the impact of the HITECH Act. The finding that hospitals were more likely to adopt MMTs in the post-HITECH Act period provides positive evidence for the expected implications of the Act.

Also, certain inherent characteristics of the hospital such as size, which represents the internal resources of the hospital act as an enabler in the adoption of MMTs and those hospitals that are short of these resources may be facing barriers to adopting MMTs. Especially, small hospitals are less likely to adopt MMTs despite the incentives of the HITECH Act. Therefore, policymakers interested in expanding the impact of the HITECH Act should pay attention to this finding and take the necessary steps to encourage adoption of MMTs among smaller hospitals. Certain unexpected findings of this study such as competition and for-profit status of hospitals being negatively associated with the adoption of MMTs also calls for the attention of policymakers and legislators. This study found that in markets with higher competition, hospitals did not prioritize adoption of MMTs. Further, another interesting finding is that contrary to expectations, for-profit hospitals were less likely to adopt MMTs. This reveals that for-profit hospitals may be experiencing certain barriers in the adoption of MMTs and that using MMTs to improve the quality of care was not a strategic priority for for-profit hospitals. This calls for the attention of policymakers towards taking steps to understand the strategic priorities of hospitals in highly competitive markets as well as among the for-profit hospitals.

Limitations of the Study

Despite the contributions of this study towards theory-driven research, methodology, policy and practice, it is important to acknowledge certain limitations that must be considered when interpreting the findings of this study.

1) The absence of a control group is a major limitation of this study. Due to this, it was not possible to control for the extraneous events that may have impacted the adoption of MMTs by U.S. acute care hospitals.

2) Another limitation of the study that arises of out of the single group study design is the inability to separate the effect of the secular trends on the adoption of MMTs from the policy implementation measure. Since the policy implementation measure is derived from the time period of implementation and there is no control group in the design, there was a collinearity between the policy implementation variable and the yearly dummy variables. Due to this collinearity, the yearly dummy variables could not be included in the models. Hence, when interpreting the results of the HITECH Act implementation, it is important to consider that the policy effect that is seen is a combination of the implementation of the Act as well as secular trends over time.
3) This study is restricted to non-CAH, non-federal, acute care hospitals located in the 50 U.S. states and the District of Columbia. Therefore, the findings of this study may not be generalizable to all hospitals in the U.S., including specialty hospitals, federal hospitals, CAHs, hospitals located in U.S. territories or other types of health care organizations.

Suggestions for Future Research

Future research could improve and expand upon the premise of this study by exploring the impact of the adoption of MMTs on outcome measures such as medication errors and adverse drug events. Although this has been examined previously, the findings from those studies are not generalizable as they focus either on one hospital or health care system or hospitals in one state. This may be due to the inability to measure medication errors on a national level. However, future research could examine the impact of adoption MMTs on broader outcomes such as financial performance, quality measures and operational efficiency of the hospitals. This will provide additional evidence for the importance of MMTs in improving the quality of health care in the country. It would also be interesting to extend this research by examining the impact of the HITECH Act on certain indirect outcomes of the Act such as improvement in the quality of care, health care costs, etc. Further, analyses similar to this study could be done to examine adoption of

MMTs in other health care organizations such as long term care facilities or specialty care hospitals.

Conclusions

The evidence from this study provides strong support for the implementation of the HITECH Act on having achieved its intended objective of promoting adoption of technologies to improve the quality of care in U.S. hospitals. With several uncertainties surrounding the benefits of the HITECH Act, this study provides an important contribution to the body of knowledge on the policy implications of the Act in this new era of health services research. This study also found that the environmental characteristic of community wealth and the organizational characteristics of size and operating margin were significantly associated with increased adoption of MMTs. Further, the environmental characteristic of competition and the organizational characteristic of for-profit status were found be significantly associated with decreased adoption of MMTs. Further, factors associated with the adoption of MMTs depended on the type of technology considered. Hospitals do not adopt all MMTs, but are strategically choosing which type of MMT to be adopted depending on its organizational and environmental characteristics. These results provide empirical support for using the resource dependence theory in examining organizational response to policy implementation and strategic behavior of innovation adoption.

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