Effects of Health Information Technology

Implementation on Clinical Outcomes and Quality of Care

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LIST OF ABBREVIATIONS

ACA	Affordable Care Act
AHA	American Hospital Association
ARRA	American Recovery and Reinvestment Act
CCD	Continuity of Care Documentation
CDS	Clinical Decision Support
CMS	Centers for Medicare and Medicaid Services
CPOE	Computerized Provider Order Entry
DICSD	Discharge Instructions and Care Summary Documents
EHR	Electronic Health Record
HIE	Health Information Exchange
HIMSS	Health Information Management Systems Society
HIT	Health Information Technology
HITECH	Health Information Technology for Economic and Clinical Health Act
ISTA	Interactive Sociotechnical Analysis Framework
ITPOSMO	Information, Technology, Processes, Objectives, Values, Staffing and Skills, Management and Structure, Other resources
MM	Medication Management
NHAMCS	National Hospital Ambulatory Medical Care Survey
PHR	Public Health Reporting
STS	Sociotechical Systems

SUMMARY

A study of the effects of Health Information Technology (HIT) on health care outcomes and quality of care was conducted to explore evidence for the relationship between different types and levels of Health Information Technology and Health Information Exchange (HIE) implementation and key healthcare outcomes. Specifically, six continuous variables representing HIT-HIE were constructed using the validated American Hospital Association's (AHA) HIT instrument. Three categorical variables were also used. A study was also conducted on the effects of HIT-HIE on Emergency Department outcomes. The first sample was drawn from CMS MedPar data from 2006-2012, for all inpatients with specific diagnoses outlined in this paper. The second study was conducted using the National Hospital Ambulatory Medical Care Survey (NHAMCS).

Overall, two out of the nine measures of HIT-HIE were found to be significantly related to adverse drug events. Discharge instructions and care summary documentation, along with clinical decision support systems (CDS) were found to be significant predictors of adverse drug events.

Furthermore, CDS was found to be the only statistically significant measure of HIT-HIE on 30 day hospital readmissions, while none of the measures of HIT-HIE were significantly associated with length of stay in the hospital, nor were they related to cost. Finally, the NHAMCS study revealed that measures of HIT-HIE revealed weakly positive effects on average length of hospital visit, and physician wait times.

SUMMARY (continued)

Overall, the benefits of HIT-HIE for care coordination were evident in adverse drug events, and hospital readmissions in the hospital setting, and length of hospital visit and waiting time to see a physician in the Emergency Department.

I. INTRODUCTION

A. Background

In recent decades, the US health care system has spent twice the average amount on health care as the average Organization for Economic Cooperation and Development (OECD) country. Despite this fact, infant mortality outcomes, along with premature mortality is higher than the OECD averages. (Organization for Economic Cooperation and Development (OECD), 2003). With increasing longevity, several factors contributed to ballooning health care costs in the US. Scholars have concluded that improvements in technology along with an aging population have been the largest contributor to increased health expenditures. (Murphy & Topel, 2003) (Marciniak, et al., 1998). Despite improvements in technology, the US health care system remained largely inefficient well into the 21st century. Fragmentation of delivery systems, lack of interoperability between information from disparate health care entities, and lack of care coordination resulted in inefficient communication among members of a patient care team, redundancies in procedures and prescriptions, and resultant adverse impacts on patient outcomes and quality of health care delivery (Berwick & Hackbarth, 2012). Furthermore, the lack of evidence of high quality care relative to other OECD countries has created a conundrum within the US whereby increases in expenditures have not lead to the outcomes expected. Numerous studies have explored the association between quality of care, health outcomes, and spending. In one such study, Yasaitas et al. found that the relationship between intensity of spending on health care, quality and care outcomes are uncertain at best, with either no or negative association between intensity of care and outcomes (Yasaitis, Fisher, Skinner, & Chandra, 2009). Intensity of care in these studies include involvement of specialists, use of intensive care units (ICU), and more diagnostic testing, resulting in little to no improvement in process-of-care quality measures

(Fisher E. S., 2003). It has been argued that investments in health information technologies will radically transform the healthcare sector by increasing efficiencies, decreasing expenditures and increasing quality of health care delivery. Prevalence of chronic diseases, and the need for improved quality of care and patient outcomes necessitates the application of Health Information Technology (HIT) and Health Information Exchange (HIE) to streamline patient care, elminate waste, and improve care coordination, with the goal of ultimately improving patient health outcomes. Health Information Technology is defined as the "application of information processing involving both computer hardware and software that deals with the storage, retrieval, sharing, and use of health care information, data, and knowledge for communication and decision making" (Brailer, 2004). This could include software applications such as electronic health records (EHRs), personal health records (PHRs) and electronic prescribing, or computerized provider order entry (CPOE) among other tools (Basics of Health IT, 2015) . Health Information Technology can also include the use of MRIs, X-Rays, CAT-Scans etc. and can be used to transfer that information to HIE. Health Information Exchanges are both an entity and process. Health Information Exchange is a means of sharing clinical and healthcare administrative data among health care practitioners and across practice settings who are not part of the same organization (Adler-Milstein, Bates, & Jha, 2011). The Health Information Management Systems Society also asserts that HIE "...assists with the transfer and sharing of health-related information that is typically stored in multiple organizations, while maintaining the context and integrity of the information being exchanged. (HIMSS.org, 2015). Health Information Exchanges consist of physical, governance and regulatory infrastructures. The physical component includes the hardware and software component described as HIT. The service component consists of the service agreements and arrangements between the stakeholders participating in the exchange of information, such as providers, hospitals, and insurance providers. The governance and regulatory component ensures that all participants and stakeholders agree to the rules and regulations surrounding the exchange of information. This governance infrastructure is what makes the process of HIE possible. The absence of rules governing the exchange of data precludes the use of HIT, and care coordination. HIT must be used with and within HIE in order to actualize the benefits of enhanced quality and health care outcomes. While MRIs and the like are types of HIT, at its core the infrastructure for the exchange of health care data and information for the improvement of care coordination, interoperability and health outcomes is HIE. In this paper, I will be using the terms jointly to describe the physical infrastructure, as well as the structures that make the exchange of information possible. This study aims to explore the effects of HIT-HIE on the outcomes and quality of care for the chronic diseases diabetes and asthma. We shall also study the effects of HIT-HIE on care associated with the following acute diseases: Acute Myocardial Infarction (AMI), Congestive Heart Failure (CHF), Hip/Pelvic Fracture and Chronic Kidney Disease, along with the effects of HIT-HIE outcomes associated with emergency department visits. The chronic conditions were selected due to the care coordination often involved in caring for patients with chronic diseases across different health care entities. The acute conditions were also selected because of the severity of the diseases, and the potential to use HIT-HIE during the patient care process. In addition, these conditions are currently tracked by the Centers for Medicare and Medicaid Services (CMS) as outcome measures of interest for measuring hospital performance and quality (Outcome Measures, 2015).

B. Statement of the Problem

Between 1965 and 2002, health care expenditures increased at a consistent and unsustainable rate of 4.5% per year (Advisors, 2013). Inefficiencies in the health care system, along with technological advances, continued to drive up health care expenditures, consuming prohibitively large portions of the US GDP. General consensus amongst researchers, policy makers and legislators is that health care costs are currently unsustainable (Advisors, 2013). As of 2011, health care costs comprised of almost 18 per cent of the GDP (Keehan, Sisko, & Truffer, 2011). Keehan et al. projected health care spending in 2020 to reach 20 per cent of US GDP (Keehan, Sisko, & Truffer, 2011). Unsustainably high health care costs reduce US competitiveness abroad, and siphon away resources that could be allocated to other areas. They also adversely affect wages and health care premiums (Agha, 2011). Numerous characteristics of the US health care system have contributed to excessive spending and waste. Inefficiencies in the process of care, overutilization of health care, administrative complexity, pricing failures and fraud and abuse are the major factors that contribute to reduced quality of care (Keehan, Sisko, & Truffer, 2011). The Congressional Budget Office (CBO) predicted that Federal spending on Medicaid and Medicare would balloon from 5 percent of GDP in 2009 to over 6 per cent in 2019, increasing the strain on both Federal and state and local governments (Elmendorf, 2009) .

Parallel to excessive waste in health care delivery is the complexity of care associated with chronic diseases and other health outcomes. Bernard and Encinosa estimate that between $25 billion and $45 billion in wasteful spending occurred as a result of lack of care coordination, particularly for the chronically ill (Bernard & Encinosa, 2004). Lack of care coordination, inadequate information at the point of care, and the vulnerability of complex, multidimensional care processes particularly amongst those with more severe morbidities are all factors that contribute to poor health outcomes (Peikes, Chen, Schore, & Brown, 2009). The American Geriatrics Society defines complexity of care as a process whereby persons whose conditions require complex continuous care and frequently require services from different practitioners in multiple settings. For example, consider the case of a person with diabetes. Diabetes mellitus is a metabolic disorder that results from the body's inability to produce and/or use insulin. Type 1 diabetes, usually classified as childhood diabetes, comprises about 5% of the entire diabetic population, and occurs when the body does not produce insulin (ADA, 2013). On the other hand, Type 2 diabetes is the most common form of diabetes, and results when either insulin production is ignored, or enough insulin is not produced by the body (ADA, 2013). As a result, glucose cannot be used as energy. Diabetes can lead to several complications, including ketoacidosis, neuropathy, eye complications, foot complications, and hypertension. As such, diabetes can be quite costly to manage for both patients and healthcare providers. Diabetes management requires consistent patient education in order to address the myriad issues, including blood glycemic control, weight management, nutrition, and medication management (LaVeist, 2003). Furthermore, the recommendations, according to the standards of medical care in diabetes include screening, diagnostic and therapeutic actions to enhance health outcomes of patients with diabetes (Standards of Medical Care in Diabetes--2013, 2015)

Persons with diabetes generally have more favorable outcomes when the disease is identified early in its inception, primary care doctors encourage and facilitate self-management, and clinicians use an interdisciplinary team approach to help manage the person's care. Often, persons with diabetes must see their primary care provider routinely, at which time they may undergo a test for hypoglycemia at each visit, along with tests for hypertension, measurement of waist circumference and body mass index, and encouragement of nutritional therapy. Persons must also undergo annual assessment of renal function, along with tests for retinopathy, dyslipidemia, and peripheral neuropathy. The complexities increase in persons with comorbidities such as Coronary Artery Disease (CAD), End Stage Renal Disease (ESRD), or other morbidities associated with diabetes. In this example, one can identify several members of the care team that may or may not be housed in a single institution. Laboratory, specialists, nutritionists and even social workers may all be included in the care team. Care may become even more complex with changes in insurance provider, insurance status, or a change in location. The potential gaps and opportunities for lapses in care increase with the complexity of the disease, increasing the potential for adverse health outcomes, and potentially increasing expenditures associated with care. This is but one example of a relatively common case of diabetes, and the opportunities for gaps in care coordination that could impact care quality and outcomes. Consider further the case of an individual with Acute Myocardial Infarction (AMI). AMI occurs when one of the arteries that supplies the heart muscle becomes blocked as a a result of a spasm of the artery or atherosclerosis (Dugdale & Chen, 2015). This results in tissue damage and loss of contraction at that portion of the heart muscle. AMI patients are most often treated in emergency departments, and often require intensive treatment prior to discharge. AMI patients are also highly susceptible to readmission within 30 days of discharge. AMI patients are particularly susceptible to high readmission rates because of comorbidities associated with other symptoms of AMI, with much of the readmissions related to subsequent heart failure. Other risks include history of smoking, previous myocardial infarction, kidney disorder and atrial arrythmia (Flynn, Lefavier, Muhyaldeen, & Ziebarth, 2015). Readmissions are costly to hospitals, particularly in light of Section 3025 of the Patient Protection and Affordable Care Act (ACA), signed into law in March of 2010, which outlines the *Hospital Readmissions Reduction Program (HRRP)* that aims to curb high readmission rates among Medicare patients. Together with inefficiency and waste in health care, these issues have resulted in a combination of poor health outcomes and excessive US health care spending and waste. (Peikes, Chen, Schore, & Brown, 2009). HIT-HIE can potentially address these issues by providing the clinician with important discharge summary information, which will ultimately be given to the patient to ensure that he/she adheres to the instructions once discharged home from the hospital. Adherence to post discharge instructions could reduce readmissions to the hospital associated with inadequate care plan adherence. Without these summaries, patients may be unclear about their discharge instructions, and clinicians may also have limited information from which to provide proper discharge instructions that take into account the patients overall health profile.

C. Purpose of Study

'Advances in medical technology have made it feasible and desirable to do more for each patient and to intervene with more patients.' (Fuchs, 1998, p. 2).

The World Bank health expenditure report lists the total expenditure for health care in the U.S. between 2009 and 2013 at 17.9% of total GDP (Bank) . Between 1965 and 2010, total national health expenditures increased at a rate of 4.5% per year (Advisors, 2013). However recent reports have shown a slow-down in health care expenditures, from 3.9% between 2000-2007, to 1.9% between 2007-2010. The Health Information Management Systems Society estimated that due to the passage of the American Recovery and Reinvestment Act of 2009

(ARRA), Over $19 billion has been allocated for hospitals and ambulatory centers for the implementation of Electronic Medical Records (HIMSS, 2009).

The Affordable Care Act (ACA) was passed amidst rapidly increasing health care expenditures, and less than desirable indicators of quality of care. Numerous inefficiencies in the health care sector resulted in reduced quality of care, and poor health outcomes. Previous literature has explored of the impact of the implementation of HIT-HIE on health care expenditures and outcomes using various methods. Agha researched the impact of HIT on the cost and quality of medical care by analyzing the trends in HIT adoption, along with other measures of technology. (Agha, 2011). McCullough et al. conducted a similar study exploring the impact of hospital IT on quality of care using specific patient outcomes and data from 2002-2007 (McCullough, Parente, & Town, 2013). The authors model the impacts of HIT on hospital outcomes by constructing patient severity measures on selected diseases in order to assess the level of care coordination requirements necessary to manage the patient's care. This paper differs significantly from McCullough et al. in that it spans a broader range of years of data, from 2006-2012 using the American Hospital Association (AHA) dataset. This allows for the analysis of patient care outcomes post ACA implementation, and well after the launch of stage 1 of Meaningful Use, which is explained below In addition, this paper also provides an analysis of HIT implementation using data from the National Hospital Ambulatory Medical Care Survey Data (NHAMCS), from 2007-2010. This allows for the analysis of patient care outcomes for patients admitted to emergency departments throughout the U.S., and covers critical years during which HIT-HIE implementation was on the upswing. It also provides survey information on critical EHR capability, along with other elements of HIT-HIE such as computerized provider order entry (CPOE), electronic prescribing, adverse drug alerts, electronic imaging, and public health reporting. These questions are relevant in consideration of the stage 1 Meaningful Use guidelines established by The United States Centers for Medicare and Medicaid Services. The guidelines are:

- Use of certified EHR in a meaningful manner (e.g., e-prescribing)
- Use of certified EHR technology for electronic exchange of health information to improve quality of health care
- Use of certified EHR technology to submit 15 clinical quality measures (CQM), such as documentation of current medications in the electronic medical record, and preventive screening for body mass index (BMI) follow-up.

In addition, hospitals are required to meet 14 core objectives:

- Computerized provider order entry (CPOE)
- Drug-Drug and drug-allergy interaction checks
- Record demographics
- Implement one clinical decision support rule
- Maintain up-to-date problem list of current and active diagnoses
- Maintain active medication list
- Maintain active medication allergy list
- Record and chart changes in vital signs
- Record smoking status for patients 13 years or older
- Report hospital clinical quality measures to CMS or States
- Provide patients with an electronic copy of their health information, upon request

- Provide patients with an electronic copy of their discharge instructions at time of discharge, upon request
- Capability to exchange key clinical information among providers of care and patient-authorized entities electronically
- Protect electronic health information

Jha (2009) reported that the four most common components of EHR are demographic characteristics, medication lists, discharge summaries and electronic clinical documentation.

In addition to the aforementioned guidelines, hospitals must have 80% of their patients with records in certified EHR technology. To date, studies such as those conducted by McCullough et al (2013), and Agha (2011) were conducted prior to the Meaningful Use launch, and as such, may miss critical information in terms of patient records and hospital engagement in meeting MU Stage 1 requirements. This study allows for responses to questions specifically regarding hospital MU participation, plans to participate, and electronic clinical documentation functionality and investment in HIT-HIE. It can be expected that the utilization of HIT-HIE to satisfy these MU requirements could lead to care coordination and improved outcomes. In that regard, this study may fill the gaps that previous studies may have encountered due to the timing of the studies prior to MU implementation.

More specifically, this study aims to determine:

1. If hospitals that have implemented HIT-HIE (according to study defined inclusion criteria) have achieved improved patient health care outcomes for high severity diseases and/or chronic conditions.

2. If the characteristics of these hospitals (large hospitals, medium sized hospitals, rural etc.) effect the success of HIT-HIE implementation and ability to meet Meaningful Use requirements.
3. The effects of HIT-HIE on improved care coordination in U.S. Hospitals
4. The effects of HIT implementation on ED efficiency measures of length of visit, waiting time to see a physician and length of stay in the hospital.

This study will also address the policy implications and areas for further research to increase the success of HIT implementation, success of HIEs and ultimately improve health care outcomes while improving the quality of health care delivery. Four propositions will serve as the foundation on which to test the empirical model for this research:

H_1: HIT-HIE as defined within this study, contributes to increased and enhanced coordination of care amongst health care providers by providing critical information at the point of care. This may contribute to a reduction in adverse drug events.

H_2: HIT-HIE improves care coordination, and clinical quality metrics at the hospital level due to increased coordination of care across disparate entities, and improved health data collection, aggregation and dissemination, and may contribute to the reduction of hospital readmissions, and reduction of hospital length of stay.

H_3: HIT-HIE may affect hospital costs and expenditures. Initial start-up costs may be very high at the outset. However, in the intermediate to long run, hospitals may see lower costs as a result of increased efficiency in the healthcare delivery process.

H_4: HIT-HIE may be particularly impactful in emergency department due to the unique constraints and processes. The necessity for timely clinical information on hand may improve emergency department efficiency metrics, such as shorter waiting time to see a physician, etc.

This paper focuses on 6 continuous variables representing HIT-HIE types of health information technology which serve as the structural quality measures. The six HIT instruments include level of implementation for electronic clinical documentation, computerized provider order entry, decision support, medication management, discharge instructions and care summary documents, and public health reporting. I also included 3 categorical measures of HIT implementation: The three categorical HIT measures used were health information exchange functionalities, regional health information exchanges (HIE) participation, and clinical summary care records. Electronic clinical documentation maintains patient records, including demographic information and physician notes. Computerized Provider Order Entry (CPOE) allows physicians and clinicians to order labs, procedures and diagnostic tests electronically. Health Information Exchange participation is an indicator of the ability of a unit, hospital or department to communicate with and exchange patient medical records with clinicians at outside institutions or with external providers. Medication management allows for electronic prescription of drugs, along with drug adverse event alerts and allergy alerts. Clinical Decision Support Systems (CDSS) provide reminders and alerts to clinicians, utilizing patient's health information and demographic characteristics to flag reminders and suggestions for screening and diagnostic tests. Clinical Care Documentation (CCD) functionality allows institutions to provide summary of care documentation among disparate institutions. Finally, electronic public health reporting allows health care institutions to exchange and submit public health immunization data, and other information to health departments. This paper explores the theoretical foundations of HIT-HIE adoption, and analyzes the effects of HIT-HIE adoption on specific health outcome measures in both the hospital and emergency department setting. The continuous healthcare outcomes of interest used for this study were length of stay, total charges accrued by the patient per hospital stay, length of visit in the emergency department, length of stay in hospital after emergency department visit, and waiting time to see a physician in the emergency department; the dichotomous healthcare outcomes used for the analysis were patient experience of an adverse drug event and patient readmission into the hospital within 30 days. The impact of the defined measures of HIT-HIE in this paper may increase coordination of care amongst providers both within institutions and across disparate institutions. Access to patient's protected health information at the point of care may inform decision-making for diagnostic tests and screening. Overall improved communication as a result of HIT-HIE implementation may improve patient outcomes and quality through better management of patient's care. This paper analyzes the impact of these various channels on health outcomes, and quality of care. I conduct empirical analyses on the effects of HIT-HIE implementation on outcomes and quality measures. I employed four regression techniques on a fixed effects model, controlling for baseline hospital characteristics and patient characteristics. To analyze effects of HIT-HIE implementation on Emergency Department outcomes and quality, I employ an OLS multivariate analysis, controlling for payer, baseline hospital characteristics, and region to determine effects of HIT-HIE on quality measures such as length of visit and physician wait times.

D. Significance

This study is significant because it analyzes the two part strategy of the US government- namely slowing health care expenditure growth through efficiency of health care delivery, while improving patient care outcomes and quality through improved coordination of care, communication, and transmission of data in a meaningful way across different institutions and providers. More specifically, this study is significant and differs from other similar research in that it utilizes the HIMSS Analytics IT Survey as a comparator database, American Hospital Association IT Survey, the National Hospital Ambulatory Health Care Survey (NHAMCS) and CMS Medicare Inpatient and Outpatient data spanning years inclusive of the launch of Meaningful Use guidelines. The fixed effects method in this study allows for the control of hospital differences to assess outcomes and quality, along with costs. Furthermore, use of the NHAMCS data set, complete with HIT applicable questions to analyze the effects of HIT on ED length of visit, length of stay and physician wait times allows us to provide an indication of the effects of HIT on length of visit, and length of stay, and it's potential to reduce excess days in the emergency department. It also allows us to measure the value of HIT/HIE for the potential coordination of EDs with other entities through discharge documentation. Similar to other studies researching effects of HIT on outcomes, the NHAMCS dataset is particularly rich and encompasses diagnoses and measures of HIT necessary to accurately assess the impact of HIT on complex and severe cases, as well as chronic diseases. Finally, functioning HIEs are emerging as the foundation through which disparate health systems, community clinics, and public health departments can exchange information, conduct disease surveillance, and allow access to current and pertinent patient health information regardless of medical home. The functions of HIT as defined in this study are all components of the health information that are made available to different networks and providers in a secure platform through HIEs. Overall, this study will contribute to the growing body of knowledge through analysis of the effects of efficient care coordination, and development of HIT/HIEs to improve patient outcomes and quality, and potentially reduce health care costs. This paper proceeds as follows. Chapter 2 provides the conceptual framework for the adoption of HIT, along with barriers to successful adoption and implementation, exploring two HIT adoption models: ITSA and ITPOSMO. This section provides a literature review that explores the historical basis for HIT implementation, interoperability and HIT, and the development of HIEs as critical to improved care coordination and enhanced patient outcomes. I also look at the issues adversely impacting health outcomes and driving up medical expenditures of which HIT/HIE implementation may have an impact-namely, overutilization of medical care, lack of care coordination, and other areas of administrative waste in health care. Chapter 3 is the methodology, which includes the data descriptions and summary. Chapter 4 provides analysis of the data and results. Chapter 5 provides interpretation of the findings, limitations and policy implications. Chapter 6 is the conclusion.

II. LITERATURE REVIEW

A. Conceptual Framework

How do we define technological change?

Theoretical literature on technological change and its impact on the health care sector are quite sparse. To fill this gap, scholars have used different proxies for technological change in order to advance the theoretical framework. Okunade and Murthy support Newhouse's hypothesis by using co-integrating regression methods to "…establish the long term relationship between expenditure on research and development in the health care sector" (Okunade & Murthy, 2002). When discussing technological change, it's important that we understand precisely how we define technological change, and its implications for determining expenditure growth and impacts on quality of care in the health care sector. Scholars have used various empirical research methods to define technological change. Conceptually, technological change may be directly associated with a transformation in the inputs and outputs, thus resulting in the formation of a new production function. This new production function typically illustrates increased factor outputs. In the health care context, this could be higher volume performed of certain procedures, or higher volume of patients seen due to increased efficiency as a result of electronic health records. Essentially, this means that using a Cobb-Douglas production function as baseline, technological change in the context of health care leads to increaesd production, as well as increasing returns to scale. In this conceptual framework, we see an embodied technological change. However, the second conceptual theory is the fact that technological change must be associated with some measure of time. This is defined as disembodied technological change. Jointly with the first conceptual theory, and within the context of this paper, one can only determine the effects of technological development on the resultant production function by including an element of time necessary to see increase in production as well as increases in expenditures. Longer studies may even demonstrate that over time, expenditures may reduce as a result of technological advances. This interaction of technological change with time means that it is not necessary to produce a new production function. Rather, there is a shift in the production function, and the technological change is disembodied from the technology. It also demonstrates the learning curve effect, where efficiency of production improves over time with increased efficiency of use of the factor inputs to increase outputs in the form of efficiency and process gains. However, the disembodied technological change may also be associated with a change in factor inputs and outputs because of its influence on the production expansion path. Within the context of this study, the technological change is considered the development of HIT and it's subsequent gradual adoption across the health care sector, until the HITECH Act mandate. The importance of the theories discused in the next section are based on the fact that adoption of new technology, and the change that follows may result in expenditure growth before the anticipated benefits of the technology are realized. Investments in technology introduce changes in organizations. These changes take time to be accepted and/or adopted by all providers. Agha (2011) analyzes differences in technological adoption by providers, finding that relatively fast adopters realized the benefits of adoption on expenditures faster than slow adopters. Slow adoption rates by providers introduce time lags between the time of investment and the realization of improvements in outcomes, cost reduction, and quality improvements. Because of these issues of technological change, we look at the empirical model of three types of technological change.

B. <u>General Model of Technological Change</u>

The first model of technological advancement stems from a study conducted by the Australian Productivity Commission. The study decomposes the determinants of expenditure growth by looking at demographic changes, income proportion of individuals with private insurance, taking into consideration moral hazard and risk aversion. The model is illustrated below:

$$\Delta E = \sum_{i=1}^{�} �_i �_i + R$$

In the above equation, ΔE is the average annual growth rate of expenditure, $�_i$ is the elasticity of the *ith* growth factor, $�_i$ is the average annual growth rate of the *ith* growth factor and R is the residual average annual growth rate (Okunade & Murthy, 2002). Ultimately, this study technological change is responsible for a range of growth between 17 to 55 per cent. (Commission, 2005). Pita Barros (1998) looked at the rates of expenditure growth among countries that started out with initially low levels of health care expenditures. His empirical results found that indeed, technological growth was a driving factor in the increase in health expenditures, interpreting the residual effects in his results as the role of health care technology in expenditure growth. Ultimately, he found that technological change explained almost 30 per cent of health care expenditure increases.

Relative Price Response and Cost Equilibrium

In the health care context, bundles of technological change could represent ‘medical management’, HIT, surgery, or other indicators of technological advancement. Because of the bundled nature of the technological change, we aggregate the relative prices and thus lose some of the granular nature of empirical analysis.

We can illustrate this conceptual theory using a classic cost-equilibrium model of health care cost for a new surgical technique to illustrate how a new technology which lowers unit costs can result in higher overall health care expenditures (Costa-Font, Courbage, & McGuire, 2009). Adopting a new surgical technique that lowers unit cost results in a substitution effect

(movement$�_1 - �$), and the output effect is a realignment of the production process such that the same expenditure can be used to increase output with change in relative price inputs.

Changes in input utilization depends on the impact that the change in relative input prices has on the marginal cost of production, since it is the interaction between marginal cost and marginal revenue, which determines the profit maximizing output. (McGuire & Serra-Sastre, 2009). Overall, we can look at the effects by using Shepherd's lemma to look at the cross-partial derivatives that are independent of the order of differentiation, illustrated by the equation below:

$$\frac{�_{�i}(�,�)}{�_{�}} = \frac{�^2 �(�,�)}{�_{�i}} = \frac{�^2 �(�,�)}{��_{�i}} = \frac{�\left[\frac{�_c(�,�)}{�_{�}}\right]}{�_{�i}}$$

$�_{�}$

In the equation above, ω is the input price and � is the total cost. We can see that the change in marginal cost caused by a change in input price equals the response of the ith input to changes in output with input prices held constant, and can be positive or negative. The *ith* input is inferior if the sign is negative, and is a normal input if the sign is positive. We know that a homothetic production function means that costs will increase with input prices if all inputs are normal, and thus we should see increased costs.

Framing the aforementioned model in the context of HIT would theoretically yield similar results. Considering elements of HIT that improve care coordination, reduce medical/prescription adverse events, and facilitate improved monitoring of patient health may initially cause an increase in factor input prices. However, over time, the realization of these benefits may effect the profit effect in that the expenditures associated with medical errors, increased length of stay, readmissions and the like will result in increased profits and reduced expenditures for hospitals and health care entities in the long run. However, technological change may not appear as a factor price change, but may be interpreted as an outward shift in the production curve.

Historical Perspective

The concept of population health is central to the role of informatics in health and medical care. Investments in health are integral to the success and functioning of entire nations. Practically speaking, healthy populations serve to increase GDP through increased output and productivity, while increased educational attainment, wealth, and potential gains in productivity serve as an incentive for individual investments in health. (Ashraf, Lester, & Weil, 2008) (Becker, 2007). Critical analysis of the parallels between health investments and productivity outlays are essential to the analysis of the importance of population health to economic productivity. More importantly, major changes in public health practice stemmed from the recognition of the importance of healthy populations to national wealth and prosperity.

Historically within the United States, Lemuel Shattuck's *Report of the Sanitary Commission of Massachusetts in 1850* became the blueprint for state and local health departments to aggressively address public health issues through the use of sanitary inspections, communicable disease control, food sanitation, vital statistics, and services for infants and children. (Shattuck, 1850). Furthermore, this report outlined many of the elements of a modern public health infrastructure. Moving from the early development of public health, William Perry argued that analysis of data could improve the health of a population through the control of communicable disease and reduction in infant mortality (Lumpkin & Magnuson, 2014). In tandem with the early collection of health data at the state and local level, scientific discoveries lead to better managed control of infectious diseases. Collection of data became central to policy and program-decision-making, and advances in sanitation, food inspection, nutrition and immunizations lead to improved public health. (Lumpkin & Magnuson, 2014).

Scholars in various industries have researched the effects of technology adoption on productivity growth. Still, scholars disagree on whether or not technology has resulted in increased and substantial productivity outlays. Whether or not technology has also increased sustainability in various industries remains a hotly debated issue. Perhaps one of the most vigorously debated issues of information technology (IT) adoption and productivity growth occurred in the manufacturing industry of the mid 1980's. The peak of this debate resulted in a remark made by economist Robert Solow-- "You can see the computer age everywhere but in the productivity statistics" (Solow, 1987). The manufacturing sector requires uniformity of production, multiregional and multinational aggregation of diverse and complex processes, for which IT is well suited. As a result, maximizing productivity requires decentralized, agile processes facilitated by IT. Similar to the manufacturing industry, the railroad industry experienced exponential productivity due to technological advances. While there is little debate about the productivity outlays as a result of technological gains, much research has explored the time lag inherent in IT adoption and productivity. Eventually, empirical evidence supported the claims that IT adoption increased productivity, while highlighting that generally, there was a lag in productivity outlays (Solow, 1987).

Over the past two decades, the health care sector has experienced an IT boom of sorts. Most recently, the passage of the Health Information Technology for Economic and Clinical Health Act (HITECH)(2009), followed by the Affordable Care Act (ACA)(2010) have placed IT front and center in the debate as to whether or not implementation of HIT can improve patient care outcomes and quality, while slowing health care expenditures. This dissertation will explore the effects of implementation of HIT on healthcare outcomes and quality, and its necessity for functioning HIEs. Health care delivery within the United States has seen increasing costs and expenditures over time, with costs increasing exponentially with technological gains. Newhouse (1992) touted technological progress with as much as 75% of the increase in health care expenditures. Not only is technological progress largely responsible for increase in health care costs, but specific technologies such as magnetic resonance imaging (MRI), computer tomography (CT) scanners, and positron emission tomography (PET) scans have impacted longevity outlays, contributing to increased longevity amongst patients. Murphy and Topel(2003) found that that longevity has increased over time as a result of technological advances , and that the economic gains of increased longevity result in higher average lifetime incomes and better health levels the closer the populations are to the onset of diseases.

Furthermore, their research suggests that population ageing and economic growth would increase the economic return to improved treatment of many diseases by almost 50 percent between 1990 and 2030 ((Murphy & Topel, 2003). Newhouse's hypothesis suggests a strong relationship between the increase in health expenditures, and increases in medical technology. Newhouse focused on several potential drivers of health care expenditure growth. On the demand side, he identified demographic ageing, insurance demand and income growth, with supply side factors supplier-induced demand and productivity differentials (Newhouse, 1992). Prior to Newhouse, Burton Weisbrod (1991) studied the effects of health care technology on expenditures, noting that post World War II, health expenditures in the US increased dramatically. However, the difference between the types of health technology employed and increased expenditures is that ultimately, initial investments in HIT may be costly for institutions. However, the continued use of HIT/HIE may be cost-saving in that it fosters efficiency in health care delivery. Citing the third party payer system and moral hazards as two driving factors of increasing healthcare expenditure, he researched the causal two-way relationship between the move from reimbursement based insurance to 'cost- incurred' or fee-for service payments which may have influenced health care providers to emphasize health care technologies that eventually drove up costs (Weisbrod, 1991). Overall, ageing populations, third party payment systems and technology investments have resulted in higer costs with marginal improvements in outcomes. However, under ARRA/HITECH(2009) and ACA(2010), the Federal government invested over $20 billion for the implementation of HIT.

C. <u>Health Information Technology</u>

Health Information Technology has developed simultaneously for health care as well as the public health sectors. The public health sector is especially reliant on communication between different entities, regular reporting and disease surveillance. As such, the benefits of HIT would be especially evident for public health. Health Information Systems within the United States developed gradually. Initially, states independently developed information systems, with standards delivered to the National Center for Health Statistics comparable for one state to another (Lumpkin & Magnuson, 2014). As states developed their own systems, other organizations such as the Centers for Disease Control and the Council of State and Territorial Epidemiologists developed standards for reporting of communicable diseases. Fragmented development of these independent systems meant that disparate data was rendered inaccessible due to lack of interoperability and standards to exchange data and information. More recently, the CDC Public health Information Network initiative was developed as a means to allow public health agencies to exchange data and information across different organizations and jurisdictions within the network (Public Health Information Network, 2014).

Julien contends that Electronic Health Records (EHR) represent the evolution and convergence of medicine and technology (Julien, 2014). The Centers for Medicare and Medicaid Services (CMS) define EHRs 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 persons care under a particular provider, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data and radiology reports. (Electronic Health Records, 2012). EHRs allow for the streamlining of clinician workflow, and encompass several core functions:

- Health information and data results management
- Order entry/management
- Decision support
- Electronic communication and connectivity
- Patient support
- Administrative processes
- Reporting and population health management

Ultimately, the primary goal of EHR is to improve patient and population health, and reduce health care costs. Julien (2014) describes continuity of care as the existence of comprehensive records over the course of the lifetime of each patient centered around the delivery of care to the patient, management of that care, and the financial, administrative and support processes that enable it. (Julien, 2014, p. 175) Access and security of protected health information (PHI) is central to continuity of care. Lack of widespread availability of electronic data is minimally functional, and presents the same barriers to higher quality care as paper charts and records. Availability of EHRs would ideally occur within the institution, and across institutions for a network of providers to maximize the benefits of EHR adoption (Julien, 2014).

Furthermore, clinicians have been notorious in the past for illegible handwritten notes and prescriptions. Bruner and Kasdan highlight the ways in which illegible physican handwriting could result in medication errors. Citing an incident where a misfiled prescription for Isordil, a drug to treat angina, was filled by the pharmacist as Plendil, a calcium channel blocker, resulting in the death of the patient. The physician was required to pay one half of the $450,000 bill, with the pharmacist paying the other half (Brahams, 1989). Bruner and Kasden further explain that not only do illegible health care documents fail to communicate important information, but they may also create potential legal problems for the physician (Bruner & Kasdan). The ability to read medication orders is essential in order for pharmacists to correctly fill prescriptions. Furthermore, the medical chart is the written narrative of all activities related to a specific patient's care. As such, the documented information in the chart, whether legible or not, may be considered valid evidence in litigation proceedings. Electronic Health Records eliminate handwritten ordering and documentation, thus reducing the risk of misinterpretation of provider orders (Julien, 2014). This method of e-prescribing is called Computerized Provider Order Entry (CPOE). CPOE minimizes risk to the patient as a result of medical errors, including reduction of adverse events stemming from negative drug-drug interactions and drug allergies, dosing and prescription errors (Julien, 2014). Despite the anticipated and perceived benefits of EHRs and HIT for continuity of care, reduction of medical errors, and availability of protected health information amongst disparate entities and providers that need that information, the adoption of HIT had been somewhat slow, with marked reluctance among health care institutions and providers. Prior to the mandates of the HITECH Act, and in order to maximize the benefits of HIT particularly for HIE, The Office of the National Coordinator (ONC), EHR vendors, and other entities needed to identify, prioritize and address the barriers and unintended consequences of successful HIT implementation. The next two sections describe some of the barriers to successful HIT implementation, along with two model frameworks of HIT implementation that have been used to address those issues.

Unintended Consequences of Health Information Technology

Currently, there are over 861 ambulatory EHR vendors with a complete EHR or EHR Module product, and 277 inpatient EHR vendors with either a complete EHR or EHR Module product (Posnack & Charles, 2014), (Posnack & Charles, EHR Certification: By the Numbers, 2015). In order to maximize the benefits of EHR systems, several key components must be addressed. The volume of EHR vendors, while allowing for flexibility in hospital and clinic choice of vendors, has had unintended consequences, particularly with regard to lack of interoperability and standards. This has created a generally siloed system whereby many hospitals can facilitate communication within the institution, but are unable to transmit or share that electronic health information with outside institutions or public health agencies.

D. Models of Health Information Technology Adoption

Interactive Sociotechnical Analysis Framework

While EHRs have the capacity to enhance quality, safety and efficiency of care, numerous studies have demonstrated that, similar to other IT projects, implementation of EHRs have unintended consequences that can prevent the ultimate success of the information system (Ash, Berg, & Coiera, 2003), (Wachter, 2006). Campbell et al.(2006) conducted a study to identify the various types of unintended consequences associated with CPOE implementation. They found that unintended consequences fell under nine categories (Campbell, Sittig, Ash, Guappone, & Dykstra, 2006):

- More/new work for clinicians
- Unfavorable workflow issues

- Never ending system demands
- Problems related to paper persistence
- Untoward changes in communication patters and practices
- Negative emotions
- Generation of new kinds of errors
- Unexpected changes in the power structure
- Overdependence on the technology

While technological issues have certainly lead to the failure of some IT projects, consideration of the sociotechnical and cultural factors that may lead to or hinder success of IT implementation is often overlooked. Sociotechnical interactions include the social, cultural and technical platform on which the IT system is built. This includes the workflow, management, and level of technological adoption at the healthcare institution (Miller & Sim, 2004), (Poon, et al., 2004) Harrison, Ross, Koppel and Bar-Lev(2007) propose the use of the Interactive Sociotechnical Analysis (ISTA) framework of technological adoption based on prior studies of unintended consequences, and research in sociotechnical systems, ergonomics, social informatics, technology-in-practice, and social construction of technology.

Studies in Sociotechnical Systems (STS) in healthcare illustrates the ways in which workflow is effected by sociotechnical forces, and its impact on patient outcomes and employee morale. Furthermore, the field of ergonomics looks at the interactions among patients, providers and the physical environment (Harrison, Koppel, & Bar-Lev, 2007). This is particularly significant in health care as most EHR systems were housed on computers in the clinician's office. Issues with lack of eye contact, physical lay-out of the room, and the positioning of the computer system that houses EHR have proven to be just a few ergonomic issues that the ISTA framework helps address. The authors attempt to create awareness of some of the barriers of successful implementation of HIT that may not be readily apparent until after HIT implementation. The dynamic and complex nature of sociotechnical interactions warrants special emphasis on the interaction types, and how HIT impacts them. Harrison et al, outline five HIT interaction types (Harrison, Koppel, & Bar-Lev, 2007):

- New HIT changes existing social system
- Technical and physical infrastructures mediate HIT use
- Social system mediates HIT use
- HIT-in-use changes social system
- HIT-social system interactions engender HIT redesign

Further study of these five interaction types provides the tools necessary for the successful implementation of HIT in healthcare organizations. This paper will review each type, along with the potential solution to address the unintended consequence. The first interaction type-New HIT changes existing social system- is the process by which implementation of HIT changes the workflow, communication process or relationships among clinicians. Often, HIT systems alter the work flow or work environment without consideration to the impact that alterations will have on communication amongst the clinical care team, and between the clinician and patient. These changes can often disrupt communication flows, or prevent timely communication between clinic personnel or worse, adversely impact patient care (Koppel, et al., 2005). Successful implementation of HIT must consider that channels of communication among the clinical care team, as well as the clinician and patient. Clear communication channels can ensure that the accuracy with which HIT enhances functions such as prescribing medications and CPOE are not offset by communication imbalances and errors resulting from poorly designed HIT systems (Campbell, Sittig, Ash, Guappone, & Dykstra, 2006).

Type 2- technical and physical infrastructures mediate HIT use results from a new HIT system that is ill-equipped to work with existing HIT systems. This often results in resistance from clinicians and staff to adopt the new system, and continue using either the existing HIT system, or paper. Clinicians may also develop workarounds in order to avoid using the new HIT system (Campbell, Sittig, Ash, Guappone, & Dykstra, 2006). This can lead to loss of data, data delays and other errors, ultimately leading to a reduction in quality of care. Furthermore, ergonomic considerations, such as the physical location of the computer housing the CPOE system can impede timely entry of data and effective communication (Koppel, et al., 2005). In order to mitigate the issues associated with type 2 interactions, HIT systems must be implemented with consideration to existing systems and workflows. User involvement and input at the earliest stages of HIT design and implementation is critical to the success of HIT implementation (Baker, Day, & Slaas, 2006). Users can provide crucial feedback and information on current work flow, communication channels, and processes among the clinical care team. They can also provide information on the optimal physical layout of HIT systems necessary to maximize face to face communication with patients as well as communication with other members of the care team (Chisholm & Ziegenfuss, 1986).

Type 3 interactions-social systems mediate HIT in-use, is closely related to type 2 interactions, in that it involves the inability of clinicians to enter critical health information in a timely fashion (Harrison, Koppel, & Bar-Lev, 2007). Harrison et al. (2007) contend that cumbersome software or HIT applications that require multiple screens and inordinate amounts of time during clinical events may lead to reduced accuracy in data entry and e-prescribing as nurses and clinicians are forced to relegate data entry to the end of the shift when more time is available to access and enter data (p.172). To mitigate this issue, HIT systems must reflect the network of social relationships among practitioners, and must take into account the time constraints under which the clinical care team must operate.

Type 4-HIT in-use changes the social system can be demonstrated in the following example: A new HIT system allows patients to be signed in electronically, after which the patient care tech brings the patient back to a waiting room. Working on a hallway freestanding HIT system, the patient care tech moves the icon indicating that the patient is now in the exam room. Seeing that the computer is occupied, another patient care tech with another patient simply bring the patient back into the waiting room, without moving the icon. As a result, the clinician for patient number 2 is unaware that the patient has been waiting in the exam room for an extended amount of time.

In this example, the patient care tech has developed a work around that adversely affects not only the patient, but also the clinician as he or she depends solely on the HIT system to receive information on whether or not a patient has checked in to his visit. As a result, the patient experiences longer than necessary wait-times, and the clinician is unaware of these circumstances. Type 4 is directly related to Type 3, in which the physical lay-out of the HIT system can change HIT-in-use, as well as the social interactions of clinical care team, clinicians and patients. Successful implementation of HIT considers the relationships among the clinical care team, as well as clinician patient relationships in its design and function.

Type 5-HIT-Social system interactions engender HIT redesign occurs when the HIT system is designed in such a way that is so divergent from the practicality of its use that clinicians or managers ignore or override signals or entry rules in order to avoid using the HIT system as designed (Harrison, Koppel, & Bar-Lev, 2007). For example, clinicians may be unwilling to use drop-down diagnoses, and as a result, may resort to free-text of diagnoses even in cases when this can cause confusion or lead to increased error. Managers may cede to this practice as opposed to enforcing the HIT functionality as designed. Type 5 further emphasizes the need for HIT systems to be designed according to the workflow, processes and communication channels of the clinical care team and patient care flow to ensure adherence to the system as designed, and mitigate unnecessary data entry, prescribing and order errors.

ITPOSMO Model

The components of the ISTA model can be analyzed with that of a the ITPOSMO model, developed by Heeks Mundy and Salazar(1999) to illustrate both the success and failure of HIT. This model is comprised of Information, Technology, Processes, Objectives and values, Staffing and Skills, Management and Structure, and Other resources: money and time. In contrast to the ISTA model, the ITPOSMO model’s broader objective focuses on conception and reality gaps that ultimately lead to failure of HIT. Heeks, Mundy and Salazar (1999) contend that failure of health care information systems (HCIS) occur as a result of change gaps between reality and the design conceptions of the HCIS. They argue that the larger the reality-conception gap, the higher the chance of HCIS failure. According to the authors, failure is classified under the following criteria (Heeks, Mundy, & Salazar, 1999):

- Total failure-a system never implemented or in which a new system is implemented but immediately abandoned.
- Partial failure- major goals are unattained or in which there are significant undesirable outcomes
- Sustainability failure-an initiative succeeds initially but then fails after a year or so
- Replication failure- an initiative succeeds in its pilot location but cannot be repeated elsewhere.

The authors highlight three types of reality gaps (Heeks, Mundy, & Salazar, 1999):

- Rationality-reality gaps, in which the way in which the HCIS is conceived is out of alignment with the realities of the organization
- Private-public sector gaps which arise from the application of public sector contexts of HCIS developed for the private sector
- Country gaps which arise from application of one country HCIS developed in a different country.

Ultimately, the degree of the reality-conception mismatch determines whether the HIT system is designed appropriately, and is an indicator of its ultimate success or failure. The first reality gap occurs when the HIT system is designed without proper regard to the organizational social and technical circumstances. This relates to the ISTA model in that improper consideration for the sociotechnical and cultural aspects of an organization when designing or implementing HIT systems can ultimately lead to failure as resistance to the new system, workarounds and lack of user buy-in prevent the HIT system from fulfilling its purpose to reduce medical errors, provider faster and more accurate health information and facilitate information exchange. The second type of reality gap-private-public sector gaps, can occur when a HIT system designed for a private sector hospital is used in a public sector hospital without modification, and vice versa. Differences between public and private hospitals are apparent in that public hospitals are more concerned with broad indicators of community health than private hospitals, whose focus is concentrated more on financial cost information. Public hospitals also tend to have less advanced technological infrastructure due to more limited funding, and have a broader case mix than private hospitals (Heeks, Mundy, & Salazar, 1999). In addition, public hospitals tend to have few technology-related staff than private hospitals, weaker non-clinical management, and less money overall than private hospitals (Vogt, Kupor, Yoshikawa, & Nakahara, 1996). Implementation of HIT systems developed for a private sector hospital in a public sector hospital are increasingly more likely to fail as the environment in which the system operates is not conducive to maximizing the benefits of HIT. Finally, country gaps can lead to failure of HIT systems based on the same principles that can lead to failure of HIT systems in public and private sector hospitals. Countries vary widely in HIT capacity, health care system infrastructure, workforce training, and political will in the healthcare system. The ITPOSMO factors must be taken into consideration when implementing HIT in order to ensure that the technology is relevant and applicable (Heeks & Bhatnagar, 1999).

Having analyzed the conceptual gaps that could potentially lead to failure of HIT, recognition of that gap closure is essential to HIT success. Heeks et al. ((Heeks, Mundy, & Salazar, 1999) argue that organizations should create maps of organizational realities in order to mitigate concept-reality gaps. The authors encourage participation of stakeholders, users, and other participants to articulate what they *should* be doing, and what they actually *are* doing. Prototypes of HIT systems can help users and designers identify and expose reality-conception gaps. Furthermore, customization of HIT systems will mitigate risks associated with “off the shelf” HIT systems that may not be appropriate for the intended organization. This is highlighted by the example of public sector vs private sector differences that can lead to reality gaps. The ITPOSMO model also de-emphasizes focus on the actual technology, and instead, similar to the ISTA model, places emphasis on the multidimensionality of HIT implementation. This multidimensionality includes the socio technical and cultural aspects of the organization for which the HIT system is intended. End-user development and participation are essential tools to the success of HIT systems. End user development ensures that along the process of design and development, the end users can provide important feedback necessary to modify the HIT systems to facilitate efficient and practical workflow and maintain open and clear communication channels among the clinical care team. Heeks et al. also suggest incrementalism as a means of introducing the HIT system gradually. This can facilitate ease in workflow, as clinicians adopt the new system gradually and incorporate the workflow steadily. This can lead to improved user satisfaction. (Heeks and Bhatnagar, 1999).

Many of the critical success factors for EHR and HIT are also applicable to HIEs, as EHRs form the foundation on which the HIE operates. However, lack of interoperability still poses an issue in terms of communication of different EHRs across entities in the care management continuum. The next section will discuss the issue of interoperability, and methods to address the issue in order to maximize HIT implementation and realize the benefits of HIE to address the problems outlined earlier in this paper.

E. Enhancing Success: Focus on Interoperability

The Office of the National Coordinator for Health Information Technology (ONC) released a groundbreaking report titled "Connecting Health and Care for the Nation: A Shared Nationwide Interoperability Roadmap Draft Version 1.0." This report outlines the goals for the majority of providers across the care continuum to "send, receive, find and use a common set of electronic clinical information" (ONC, 2014). In addition to the report focus on individuals and care providers, it's usefulness includes community-based services, social services, public health and researchers (ONC, 2014). This report also highlights several issues with electronic health information that present barriers to maximization of the use of that information to improve patient outcomes and reduce costs. Lack of standardization and structure of electronic health information means that often end users are unable to parse and access the data. This also presents barriers to automation of the health information. Other key issues are centered around the need to build trust amongst disparate networks in a systematic way, while reaching a level of understanding with regard to the laws and policies surrounding electronic information sharing. ONC relies heavily on the concept of a "learning health system" as the model for interoperability and information exchange going forward. This concept was originally developed by the Institute of Medicine (IOM) in 2005, in response to the need to enhance patient safety, efficiency and quality of care (Medicine, Institute of (IOM), 2007). Perhaps most significant about this new model of learning health put forth by ONC is its focus on a health ecosystem, as opposed to health care delivery in the hospital setting. The health system is described as "...an ecosystem where all stakeholders can securely, effectively and efficiently contribute, share and analyze data and create new knowledge that can be consumed by a wide variety of electronic health information systems to support effective decision-making leading to improved health outcomes" (ONC, 2014).

Rather than viewing public health, clinical research and clinical care as separate entities, they are viewed as interrelated entities that mutually rely on each other to optimize health across the care continuum (ONC, 2014). Recognizing the immense impact that HIT could have on the healthcare sector, and as part of ARRA, HITECH provided several grants and incentives to use HIT to improve clinical care, reduce healthcare costs and support population and public health (Magnuson & Fu, 2014). Ultimately the goals of HITECH are to improve individual and population health outcomes, increase transparency and efficiency and improve the ability to study and improve care delivery (Blumenthal, 2010). In order to achieve these objectives, HITECH is centered on several action items. Adoption of EHRs is the first step to improving individual and population health outcomes. Regional Extension Centers (RECs) serve as the channel by which hospitals and community clinics could receive training and support for EHR implementation. (Electronic Health Records, 2012). Finally, the Office of the National Coordinator for Health Information Technology (ONC) developed a set of meaningful use guidelines enabled by Medicare and Medicaid to provide incentives and penalties for the "meaningful use" of HIT (Meaningful Use Regulations, 2014). The final step in the process of maximizing HIT to achieve the aforementioned objectives is the provision of state grants for the formation of Health Information Exchanges (HIE). Congress appropriated more than $30 billion in incentives to support HITECH (Jha, 2010). Furthermore, CMS has put forth several initiatives to facilitate enhanced care coordination and communication across care providers, all for which HIT is an integral component (CMS.gov, 2015). One such initiative is the Bundled Payments for Care Improvement Initiative. To illustrate the link between fragmented care and higher costs, Medicare has historically paid providers for individual services for a single illness or course of illness. Launched in 2013, this initiative allows organizations to enter into payment arrangements that include financial and performance accountability for episodes of care, in order to facilitate better quality and better coordinated care at lower costs (CMS.gov, 2015). The bundled payment system facilitates lower costs and better care in that it aligns provider incentives to coordinate with members of the care team. Participating organizations enter payment arrangements that hold them accountable for the financial and quality performance for episodes of care. Other scholars have researched alternative methods of achieving similar ends through coordination of Accountable Care Organizations. The Centers for Medicare and Medicaid Services (CMS) define Accountable Care Organizations (ACOs) as a group of doctors, hospitals and other health care providers, who come together voluntarily to give coordinated high quality care to their Medicare patients (Accounable Care Organizations, 2014). They further contend that “the goal of coordinated care is to ensure that patients, especially the chronically ill, get the right care at the right time, while avoiding unnecessary duplication of services and preventing medical errors” (Accounable Care Organizations, 2014). ACOs encourage better coordinated care as a means for reducing duplication of procedures, enhancing patient care outcomes, and reducing re-admissions. Other strategies used to foster improved coordination of care include the shift to bundled payment systems such as Pay for Performance (P4P), and community-based care transition programs (Accounable Care Organizations, 2014).

F. Health Information Exchanges: Integral Role in Care Coordination

Conceptually, the sharing of healthcare information across entities occurred prior to the development of EHRs through the transfer of paper forms systems to exchange information across healthcare, insurance, billing and public health institutions. Later on, asynchronous data exchange such as tape reels, hard drives and flash RAM developed, eventually evolving into synchronous exchange through ISDN connections and telephone lines (Magnuson & Fu, 2014). The inefficient means by which health information was transferred was particularly troublesome for public health. Public health requires timely information, in order to address urgent public health needs. This prompted the Institute of Medicine in 1988 to release the report "The Future of Public health" which strongly critiqued the public health infrastructure as "outdated and vulnerable technologies; a public health workforce lacking training and reinforcements; antiquated laboratory capacity; lack of real-time surveillance and epidemiological systems; ineffective and fragmented communication networks; incomplete domestic preparedness and emergency response capabilities; and communities without access to essential public health services." (National Research Council, 1988). This report spawned the development and funding of public health infrastructure that would ultimately lead to the development of HIEs.

American Recovery and Reinvestment Act, Health Information for Technology and Economic Clinical Health Act, and Health Information Exchange Funding

The American Recovery and Reinvestment Act (ARRA) of 2009 formed the Health Information Technology for Economic and Clinical Health (HITECH) Act, which provided incentives, grants and programs to increase the use of health information technology for the reasons stated above. (Health IT Legislation, 2014). With the advent of Accountable Care Organizations, and as the U.S. health care system seeks to find new ways to reduce health care costs and increase patient quality, many institutions have implemented EHR as a means of tracking disease symptomology, conditions, treatments and outcomes over time. This information can improve population health in the long run as it provides a profile of whole communities and populations to inform evidence-based medicine. EHR is also especially useful for public health reporting through tracking outbreaks, syndromic surveillance, immunization, and electronic reporting of lab results (Julien, 2014).

Early Health Information Exchanges

Community Health Information Networks (CHINS) were established in the 1980s as a means of exchanging information across different entities in the community during a period of time where very few organization had functional IT systems capable of exchanging information. CHINS were replaced with Regional Health Information Organizations (RHIO), which allowed different healthcare entities within a particular region to share clinical and administrative health data (Magnuson & Fu, 2014). Regional Health Information Organizations presented challenges in and of themselves. The lingering challenges of network effect, in which an entity becomes more effective as more users enter the network proved to be a barrier in the success of RHIOs. Other issues included the need for appropriate leadership, maintenance of privacy and security of protected health information (PHI) and lack of interoperability and standards. Finally, HIT systems require funding, which was often difficult without sufficient stakeholder buy-in, and without a clearly demonstrated return on investment (Lumpkin & Magnuson, 2014) (Magnuson & Fu, 2014).

Nation-Wide Health Information Network and Health Information Exhcanges

In 2001, the National Institute on Vital and Health Statistics drafted a report articulating the need for a framework of principles, standards, procedures and policies to facilitate and coordinate the exchange and use of health information (Institute of Medicine, 2001). The Institute of Medicine then defined the need for a National health Information Network (Institute of Medicine, 2001). The National Health Information Network (NHIN) would ultimately be a network of interoperable health IT systems spanning the United States that would provide the seamless transfer of PHI across institutions (Institute of Medicine, 2001). The case for the NHIN was based upon studies that demonstrated that despite high operational and start-up costs, the down-stream efficiencies and cost savings would be well worth the investment (Walker, et al., 2005) Currently, HIEs have begun to transform the landscape of provision of care in the United States. Previously, patients would often transfer their medical records to different providers, increasing the chance for medical and prescribing error, while creating lag times that ultimately reduced quality of care. The widespread availability of electronic data transfer improves the quality, safety and cost of patient care by allowing providers to have ready access to a patient's medical records, avoid physician errors, improve diagnoses and reduce duplicate testing (Walker, et al., 2005) HIEs exchange information through three methods:

- Directed Exchange-ability to send and receive secure information electronically between care providers to support coordinated care
- Query-based Exchange-ability for providers to find and/or request information on a patient from other providers, often used for unplanned care
- Consumer mediated Exchange-ability for patients to aggregate and control the use

of their health information among providers

Areas of Waste in Health Care

Much of health care expenditure, along with poor health outcomes, can be attributed to various forms of waste in health care (Berwick & Hackbarth, Eliminating Waste in US Health Care, 2012). In this section, I will explore the factors that lead to waste in healthcare, resulting in increased expenditures and poor outcomes. Scholars categorize and measure waste using various metrics. Categorizing health care waste into administrative, clinical and operational waste, Bentley et al. found that health care waste occurs as a result of health insurance and medical uncertainties, and the low-quality care and poor outcomes that result (Bentley, Effros, Palar, & Keeler, 2008). Still, Reinhardt et al. Take a broader look at the areas of waste in health care by conducting an in depth comparison of the US health care system relative to other OECD countries. While they cite high administrative costs, the researchers also point to the facts of higher GDP-ultimately, higher ability to pay leading to higher health care costs. The authors also point to the fact that Americans pay more for health care services in the US than citizens from other countries. They also found that “About 90 percent of the observed cross-national variation in health spending across the OECD countries in 2001 can be explained simply by GDP per capita” (Reinhardt, Hussey, & Anderson, 2004). Put simply, the ability of a higher volume of US citizens to pay for care relative to other populations accounted for about 90 percent of the variation in health care spending.

First, I explore the use of unnecessary medical services, or overutilization. Next, look at the inefficient delivery of health care services, and how this leads to excessive waste and spending. Finally, I cover high administrative costs of care, followed by inadequate focus on prevention and public health strategies.

Care Coordination and Continuity of Care

Care coordination involves the organization of patient care activities, along with the sharing of information among all the participants involved in the patient's care (Agency for Healthcare Research and Quality, 2014). The Institute of Medicine attributes care coordination as an important method to improve the effectiveness, safety and efficiency of the health care system (Adams & Corrigan, 2015). Furthermore, IOM prioritizes care coordination across all priority areas related to behavioral health, chronic conditions, preventive health, and care related to the end of life. Effective care coordination is essential to communicate information to all providers involved in the patient's care at the appropriate time. This information is used to guide and deliver high-quality patient care and achieve quality outcomes. Berwick and colleagues provide an excellent analysis of the importance of coordination of care to fulfill what they call the triple aim: "Improving the individual experience of care; improving the health of populations; and reducing the per capita costs of care for populations" (Berwick, Nolan, & Whittington, 2008). Coordination of care documentation, medication management, and team communication are all facets of patient care coordination for which HIT may prove benefiticial. Perhaps most important in coordination of care is the ability to monitor patient's needs both in and outside of the hospital. The hospital readmissions within 30 days metric is used to monitor and penalize those hospitals that experience high rates of hospital readmission within 30 days of discharge, and will be discussed further in the next section. It's relevance to coordination of care lies in the fact that hospitals and clinician's ability to communicate with outpatient facilities, community clinics ,pharmacies or other entities to assist the patient in self-management upon discharge may have implications for readmission within 30 days of discharge. More specifically, care coordination may involve coordination of transitions of care, the provision of continuity of care documentation, development of an effective care plan, connections to community clinics and resources, and aligning resources with the patient's needs. Furthermore, the continuum of care may involved hospitals, dialysis centers schools, community clinics, and even homes. The diversity of settings and providers warrant a closer look at ways to enhance care coordination. Later in this paper I will explore the potential role of HIT in enhancing care coordination.

Coordination of care is especially important for chronic disease management, preventive care as well as increased disease severity. Patients with chronic illnesses require increased frequency of clinician visits, tests, and other procedures associated with care. While this may vary from geographic region to geographic region and health care organization, the overall trend is that patients with chronic illness require enhanced communication between themselves and the clinical care team, as well as communication amongst the clinical care team at diverse institutions (Culler, Parchman, & Przybylski, 1998). Patients with chronic conditions, in addition to those with severe illnesses, require efficient care coordination to ensure favorable outcomes. Care coordination may involve the transfer of information from providers in external networks, transfer of patient health information across different care teams, as well as disbursement of continuity of care documentation and discharge instructions to both the patient and the primary care provider. Piekes et al. conducted an observational study of 15 opt-in care coordination programs for Medicare patients. Utilizing hospitalization, costs, and some quality-of-care outcomes measures, the authors concluded that programs with in-person contact targeted towards moderate to severe patients can be cost-neutral and improve some aspects of care. While not compelling, this work demonstrated the potential that coordination of care and effective communication with patients can have on outcomes as well as health care costs. Supplysensitive care for chronically ill patients towards the end fo life also effects care outcomes, and health expenditures. This also varies from region to region. Nyweide et al. conducted a retrospective cohort study of fee-for-service Medicare beneficiaries over age 65 with at least 4 ambulatory visits in 2008. They found that the effects of continuity of care and preventable hospitalizations in older adults, with occurrence of preventable hospital admissions as the outcome measure of interest. They authors concluded that among fee-for-service beneficiaries older than 65 years, higher continuity of ambulatory care is associated with a lower rate of preventable hospitalization. (Nyweide, et al., 2013). This study and others continue to highlight the benefits of care coordination on patient outcomes and health care expenditure reduction (Christaikis, Mell, Koepsell, Zimmerman, & Connell, 2001) (Centers for Medicare and Medicaid Services, 2015) (Jee & Cabana, 2006).

Overall, there exists a wealth of literature concerning the adoption of information technology and conceptual frameworks to maximize the beneficial outcomes of the technology adoption. I have also briefly explored the mechanisms driving health care expenditures and potentially driving less than ideal quality of care outcomes. This paper adds significant value to the field in that it outlines in great depth the major factors surround technological adoption, HIT implementation, the US health care system, and opportunities for improvement in health outcomes and quality. While many studies have focused solely on the health care system in the context of the hospital, this study focuses not on the hospital context, but the potential for community clinics, public health entities and other stakeholders to participate and maximize the benefits of HIT implementation through HIEs. It also provides insight into the effect that the

ACA will have on future health care costs and outcomes, as it encompasses years pre and post meaningful use implementation.

III. METHODOLOGY

This study used ordinary least squares (OLS) regression, logistic regression, and negative binomial regression to assess the effects of measures of HIT on specific health care delivery outcomes. This study also uses logistic regression to assess the effects of EMR on emergency department quality outcomes. The independent variables were (a) adverse drug events, (b)30 day hospital readmissions and (c) length of stay. For the NHAMCS data set, I employ a multivariate logistic regression on longitudinal survey. The outcomes of interest were length of visit, wait time to see a physician in the hospital, and length of stay in the hospital. The dependent variables were the measures of HIT described below. Given the richness of the data sources and the large sample size, it was important to design the study in order to maximize those attributes. This chapter begins with a description of the inclusion criteria for CMS patients and the sample size. I then define the measures of HIT used in the study, followed by a description of the data sources. Next, I provide a statement about the validity and reliability of the study, followed by the empirical research design and the empirical models employed.

A. Justification of Structural Quality Measures and Inclusion Criteria

I focus on a mix of high severity diagnoses as well as chronic conditions. I focus on five high severity conditions: Acute Myocardial Infarction (AMI), Renal Failure, Congestive Heart Failure (CHF), Hip/Pelvic Fracture and Chronic Kidney Disease. I selected these diseases because the severity of the diagnosis typically warrants communication across a diverse team of care providers, some of whom may practice at different hospitals and require enhanced coordination of care and communication. I also chose the following chronic disease diagnoses: Diabetes and Asthma. I selected these chronic conditions because they can also provide insight on the use of HIT to coordinate care due to repeated visits for maintenance of care, as well as the potential for physician counseling for chronic disease management (Standards of Medical Care in Diabetes--2013, 2015). Finally, I measure the effects of HIT on quality by looking at the following outcome measures: 30 day readmission rates, length of stay, and adverse drug events. For the NHAMCS, I look at effects of EMR/EHR on length of visit, length of hospital stay, and physician wait times.

B. Sample Construction

Using hospital ID, I link the AHA IT supplement to a sample of 100,000 CMS Medicare inpatient and outpatient claims patients over a span of 6 years, 2006-2012. The Medpar data is particularly rich for my analysis. It consists of the Medicare Base Files, Chronic Conditions and Cost and Use files for inpatient, outpatient, SNF, and Part D Event (with drug characteristics variables). By linking these data sources, I construct hospital quality metrics and measures of patient health. The CMS sample includes patients admitted to the hospital with a primary diagnosis of congestive heart failure, acute myocardial infarction, hip and knee fracture, chronic kidney disease, diabetes and asthma, including all inpatient and outpatient Medicare claims for one year. CMS currently reports 30 day mortality measures for AMI, CHF and Hip and Knee Fracture, along with 30 day risk-standardized readmission measures for AMI, HF, Hip Fracture and Chronic Kidney Disease. The nature of these diseases, along with severity serves as a good indicator of disease incidence. CMS justifies these conditions on the basis that "Publicly reporting these measures increases the transparency of hospital care, provides useful information for consumers choosing care, and assists hospitals in their quality improvement efforts" (CMS.gov, 2015). In addition to these patients, I analyze services provided for patients diagnosed with diabetes and asthma. This lends validity to my study because severity of diagnosis can have implications for the dependency on HIT/HIE via continuity of care documentation (CCD), and enhanced coordination of care through HIE to effect outcomes for patients with chronic diseases. I define patient exposure to HIT according to the adoption status of the hospital to which the patient was admitted and received inpatient treatment. Data spans the years 2006-2012. This also differs from previous research because it not only captures pre and post HITECH and ARRA, but also captures the early days of Meaningful Use guideline adoption.

Measures of Health Information Technology Adoption

Based on research on various measures of HIT and Meaningful use guidelines, and impact on quality of care and health outcomes, I have defined HIT adoption highlighting the elements of HIT defined below:

Electronic Health Records

Electronic Health Records can potentially reduce waste because they allow for timely access of patient medical records at the point of care, rather than delays in care to allow patients to obtain medical records from other institutions

Clinical Decision Support

Clinical Decision Support is essential to preventive care. It helps providers interpret clinical results, document patients' health status, and prescribe medication through the use of alerts, reminders and customized data entry forms (Clinical Decision Support (CDS) Initiative ,

2014) CDSS can be instrumental in preventing unnecessary hospitalization and adverse events by providing the physician with critical patient information at the point of care, and providing a profile of the patients’ medical history without the need to request separate medical records from other providers.

Computerized Provider Order Entry

Computerized Provider Order Entry allows providers to enter medication orders and other instructions electronically. It is beneficial in the care process because it helps reduce medical errors resulting from illegible handwriting in paper charts, and tracks orders electronically.

Health Information Exchange

Health Information Exchanges are also crucial to preventive care. Oftentimes, patients, particularly those with chronic diseases, may visit several different care providers. In cases of emergency or hospitalization, they may be admitted at an institution that does not serve as their primary institution of care. Paper records can make coordination of the patients care, accurate medical history and accurate prescription of medications difficult (Health Management Associates, Inc., 2011). Risks of adverse drug interactions, medication allergies and lack of information on chronic disease patients can result in increased medical errors. HIEs provide a platform by which clinicians can exchange and access patient records through a direct node, without waiting for clearance from medical records departments if the potential users are authorized to see the records). In this way, clinicians have access to their patients’ health profile, and can thus make better decisions about the patient’s care.

Continuity of Care Documentation

The Continuity of Care Document provides a patient summary, medication and allergy lists and patient demographic information. This document facilitates transfer of care between clinicians, which can be crucial in preventing re-admissions, which ultimately drive up health care costs.

Public Health Reporting

Public Health Reporting was included as a HIT measure because health care institutions are often required to report selected diagnoses to local public health departments. This is important for disease surveillance, contact tracing, and for the health department to have an overall view of the community health profile. To that end, it is critical that health care institutions are able to conduct timely and efficient public health reporting requirements.

Medication Management

Medication management was included because of the potential for patients who are seen at different facilities to receive duplicate prescriptions, or experience other areas associated with lack of information about the patient's medication history. Medication reconciliation is important for the prevention of adverse drug events. It's also critical for physicians at the point of care to be aware of any allergies to medications, particularly if the physician is not familiar with the patients' medical history.

Discharge Instructions and Care Summary Documents

Discharge Instructions and Care Summary Documents are important in this study because it documents whether or not clinicians provide summary of care documentation in an electronic format accessible to the patient. This has implications for the care that a patient may receive at a different facility. Accessing this information electronically could be useful for providers at disparate facilities and assist them in identifying the discharge and summary of care instructions for the patient. This could potentially help reduce duplication of procedures.

Data Sources and Description

To conduct this research, I use the Health Information Management Systems Society (HIMSS) IT database as a comparator, coupled with the American Hospital Association (AHA) Hospital survey data. I then combine this data with a sample of 100,000 patients from the CMS Medpar data from 2006-2012, along with the standard Medicare file of patient claims for 2006-2012 as the control cohort.

The HIMSS analytic data encompasses data on HIT-HIE functionalities such as Electronic Medical Record (EMR), Computerized Provider Order Entry (CPOE), Health Information Exchange (HIE) participation, and other components of HIT. This annual survey covers IT use on nearly 5,400 U.S. hospitals and more than 26,000 ambulatory facilities that are associated with these hospitals. It is the longest running HIT survey in the U.S., and includes other information such as market segmentation and size statistics, IT purchase plans for health care organizations and software, hardware, and infrastructure installed throughout all facilities. One limitation of the HIMSS survey data is that it does not offer insight into the level of functionality of HIT upon implementation. For this study, the HIMSS database is mainly used for comparison to the AHA database on specific HIT measures for those hospitals that are included in both studies. I also use the 2013 AHA Hospital IT survey for this study. The AHA IT survey is an annual survey with data from 3200 hospitals, and includes information on HIT indicators that it illustrates the level of HIT integration in hospitals. It covers elements such as electronic clinical documentation, results viewing, decision support, drug alerts, pharmaceutical tracking and HIE participation. The significance of the AHA IT survey is that it not only illustrates the level of participation of the participating institutions, but also provides insight into the barriers to implementation in key areas, as well as the level of functionality of the HIT installation. It also serves as the foundation for research for the Office of the National Coordinator for Health Information Technology, and an over 50 per cent response rate makes it particularly resilient to sampling bias. It compliments the HIMSS data in that it provides information on hospital characteristics, as well as details about the functionalities of the HIT components. For example, while the HIMSS database tells us whether or not a hospital participates in HIE, the AHA IT survey gives us more details on the actual HIE linkage, time of participation, and whether or not the hospital is actively channeling information through the HIE. One limitation of the AHA annual IT survey database is that it does not include as broad a hospital base as the HIMSS database. Also, the survey dates back to 2008. Despite the relative recency of the survey, the question and survey design are such that respondents are still able to indicate clearly the year of HIT implementation as a continuous variable. The specific variables used in this study are as follows:

Values 1 – 6

Key

1 = Fully implemented across all units

2 = Fully implemented in at least one unit

3 = Beginning to implement in at least one unit

4 = Have resources to implement in the next year

5 = Do not have resources but considering implementing

6 = Not in place and not considering implementing

Electronic Clinical Documentation Q1_A1 to Q1_G1

Does your hospital currently have a computerized system which allows for:

a. Q1_A1 Patient demographics (doc.)

b. Q1_B1 Physician notes (doc.)

c. Q1_C1 Nursing notes (doc.)

d. Q1_D1 Problem lists (doc.)

e. Medication lists Q1_E1 Medication lists (doc.)

f. Discharge summaries Q1_F1 Discharge summaries (doc.)

g. Advanced directives (e.g. DNR) Q1_G1 Advanced directives

Computerized Provider Order Entry (CPOE) Q1_A3-Q1_E3

Computerized provider order entry (Provider (e.g., MD, APN, NP) directly enters own orders that are transmitted electronically)

a. Q1_A3 Laboratory tests

b. Q1_B3 Radiology tests

c. Medications Q1_C3 Medications

d. Consultation requests Q1_D3 Consultation requests

e. Nursing orders Q1_E3 Nursing orders

Decision Support Q1_A4-Q1_F4

Decision support

a. Clinical guidelines (e.g. Beta blockers post-MI, ASA in CAD) Q1_A4 Clinical guidelines
b. Q1_B4 Clinical reminders((e.g. pneumovax))

c. Q1_C4 Drug allergy alerts

d. Drug-drug interaction alerts Q1_D4 Drug-drug interaction alerts

e. Drug-Lab interaction alerts Q1_E4 Drug-Lab interaction alerts
f. Drug dosing support (e.g. renal dose guidance) Q1_F4 Drug dosing support

Key

1 = Yes

2 = No

3 = Do not know

Medication Management Q2_A3-Q2_E3

Medication Management

a. Compare a patient's inpatient and preadmission medication lists Q2_A3 Compare patient's inpatient & preadmission med. list

b. Q2_B3 Provide updated med. list at discharge

c. Q2_C3 Check inpatient prescriptions against internal formulary

d. Q2_D3 Automatically track medications with eMAR

e. Q2_E3 eRx of discharge medication orders

Discharge Instructions and Care Summary Documents Q2_A4-Q2_F4

Discharge Instructions and Care Summary Documents

a. Q2_A4 Electronic copy of discharge instructions upon request

b. Q2_B4 Electronic copy of record upon request

c. Q2_C4 Summary of care record for relevant transitions of care

d Q2_D4 Include care teams and plan of care in care summary record

e Q2_E4 Electronically exchange key clinical information with providers

f Q2_F4 Transition of care summaries to an unaffiliated org using different certified EHR vendor

Public Health Reporting Q2_A6-Q2_C6

Public Health Reporting

a. Submit electronic data to immunization registries or immunization information systems per meaningful use standards Q2_A6

b. Submit electronic data on reportable lab results to public health agencies per meaningful use standards Q2_B6

c. Submit electronic syndromic surveillance data to public health agencies per meaningful use standards

Q2_C6

Health Information Exchange Functionalities Q4_A

4a. Do any current arrangements exist in your area to share electronic patient-level clinical data through an electronic health information exchange (HIE) or a regional health information organization (RHIO)?

Electronic sharing of patient-level clinical data Q4_A

Key

1 = Arrangement(s) exist(s)

2 = Arrangement(s) do(es) not exist

3 = Do not know

Question 4B HIE Q4_B

4b. Please indicate your level of participation in a regional health information exchange (HIE) or regional health information organization (RHIO)

Level of HIE or RHIO participation Q4_B Level of HIE or RHIO participation

Key

1 = Participating and actively exchanging data in at least one HIE/RHIO

2 = Have the electronic framework to participate but not participating in any HIE/RHIO at this time

3 = Do not have the electronic framework to participate and not participating in any HIE/RHIO at this time

4 = Do not know

Question 3c Q3_C

3c. Does your hospital have the capability to send clinical/summary of care records in Continuous Care Record (CCR), Clinical Document Architecture (CDA) or Continuous Care Documentation (CCD) format?

Key

1 = Yes

2 = No

3 = Do Not Know

4 = Not applicable

Question 11, IN what year did you deploy your EHR/EMR Q11

11. In what year did you first deploy your EHR/EMR?

Key

YEAR

1 = Do not know

C. Validity and Reliability of AHA IT Supplement

In order to determine the validity and reliability of the AHA data, we conducted exploratory analysis using a Principal Component Analysis extraction method coupled with Varimax with Kaiser Normalization. All of the variables included in this study were determined to be valid and reliable. This is further documented by Everson, Lee and Friedman (Everson, Lee, & Friedman, 2013). They evaluated the internal consistency, construct valiadity and criterion validity of the items measuring IT adoption in the AHA IT supplement. They concluded that five out of six functionalities produced reliable scales, and that the instrument is both reliable and valid.

The final data source is a secondary analysis of data collected in the National Hospital Ambulatory Medical Care Survey (NHAMCS).

> "The NHAMCS is an annual, national probability sample of ambulatory visits made to non-federal, general, and short-stay hospitals in the U.S. conducted by the Centers for Disease Control and Prevention, National Center for Health Statistics. Although the survey includes visits to selected ambulatory care departments, this analysis focuses solely on the visits to hospital emergency departments (EDs). The survey has been conducted annually since 1992 (CDC, 2015). The multi-staged sample design is composed of 3 stages for the ED component: (1) 112 geographic primary sampling units that comprised a probability subsample of primary sampling units from the 1985 to 1994 National Health Interview Surveys; (2) approximately 480 hospitals within primary sampling units; and (3) patient visits within emergency service areas. Sample hospitals are randomly assigned to 16 panels that rotate across 13 4-week reporting periods throughout the year, with each hospital being surveyed once every 15 months (CDC, 2015). The initial sample frame of hospitals was based on the 1991 SMG hospital database now maintained by IMS Health.
>
> Hospitals are inducted into the NHAMCS by field representatives of the U.S. Census Bureau. Hospital staff or Census Bureau field representatives complete a patient record form for each sampled visit based on information obtained from the medical record. The data collected include information on patient demographics, reasons for visit, vital signs, cause(s) of injury, diagnoses rendered, diagnostic tests ordered, procedures provided, medications prescribed, providers consulted, and disposition including hospital discharge information if

> admitted (since 2005). Approximately 95.1% of sampled hospitals participated annually in the survey, and about 92% of sampled EDs provided complete information on their sample visits for a total un-weighted response rate of 87.5%" (McCaig & Burt, 2012).

The NHAMCS is approved annually by the Ethics Review Board of NCHS. The Ethics Review Board grants waivers for informed consent requirements for the authorization and release of patient medical record data.

Data processing, including medical coding of reason for visit, cause of injury, diagnosis, and medications are performed by SRA International, Inc., Durham, NC. As part of the quality assurance procedure, a 10% quality control sample of PRFs is independently keyed and coded (Hsiao, Cherry, Beatty, & Rechsteiner, 2010). Error rates typically range between 0.3% and 0.9% for various survey items. This study covers 2007-2010. All hospitals in the survey are included in this analysis. Among the survey questions include the following questions related to HIT:

- Does your ED submit claims electronically (electronic billing)?
- Does your ED use electronic medical or health records (EMR/EHR) (not including billing records)?
- Does your ED have a computerized system for patient demographic information? If yes, does this include patient problem list?
- Does your ED have a computerized system for clinical notes?
- If clinical notes are included, do they include a list of medications that the patient is taking?
- If clinical notes are included, do they include a comprehensive list of the patient's allergies?

- Does your ED have a computerized system for orders for prescriptions?
- If yes, are there warnings of drug interactions or contraindications provided?
- If yes, are prescriptions sent electronically to the pharmacy?
- Does your ED have a computerized system for orders for tests? If yes, are orders sent electronically?
- Does your ED have a computerized system for viewing of lab results?
- If viewing of lab results are included, are results incorporated in EMR/EHR? If yes, are out of range values highlighted?
- Does your ED have a computerized system for viewing of imaging results?
- Does your ED have a computerized system for reminders for guideline-based interventions and/or screening tests?
- Does your ED have a computerized system for electronic reporting to immunization registries?
- If orders for press/lab tests submitted electronically, who submits them: prescribing practitioner – unedited?
- If orders for press/lab tests submitted electronically, who submits them: other clinician – unedited?
- If orders for press/lab tests submitted electronically, who submits them: lab technician – unedited?
- If orders for prescr/lab tests submitted electronically, who submits them: admin pers – unedited?
- If orders for prescr/lab tests submitted electronically, who submits them: other personnel – unedited?

- Orders for prescriptions and lab tests not submitted electronically – unedited?
- If orders for prescr/lab tests submitted electronically, who submits them: unknown – unedited?
- If orders for prescr/lab tests submitted electronically, who submits them: prescribing practitioner – edited?
- If orders for prescr/lab tests submitted electronically, who submits them: other clinician – edited?
- If orders for prescr/lab tests submitted electronically, who submits them: lab technician – edited?
- If orders for prescr/lab tests submitted electronically, who submits them: admin pers- edited?
- If orders for prescr/lab tests submitted electronically, who submits them: other personnel – edited?
- Orders for prescriptions and lab tests not submitted electronically – edited?
- If orders for prescr/lab tests submitted electronically, who submits them: unknown – edited?
- Does your ED have plans for installing a new EMR/EHR system within the next 18 months?
- Does your hospital have plans to apply for Medicare or Medicaid incentive payments for meaningful use of Health IT?
- What year does your hospital expect to apply for the meaningful use payments?

These survey questions are valuable in order to help solidify our understanding of the extent of EMR use in the Emergency Department, and the effects of HIT-HIE on measures of ED efficiency and quality. The survey data were analyzed using the sampled visit weight that is the product of the corresponding sampling fractions at each stage in the sample design. The sampling weights have been adjusted by NCHS for survey nonresponse within time of year, geographic region, urban/rural and ownership designations, yielding an unbiased national estimate of ED visit occurrences, percentages, and characteristics. Because of the complex sample design, sampling errors were determined using SAS SVY PROCS. Initially, there was a total of 139502 total ED visits. I dropped 98361 visits due to missing or invalid information for wait time, length of visit, or length of stay. A total of 41141 observations remained in the sample. I focus on wait time to see a physician, length of visit, and length of stay as measures of efficiency outcomes. In accordance with meaningful use guidelines established by the Office of the National Coordinator, I group 6 individual elements of HIT to serve as a measure of HIT adoption in the ED (Centers for Medicare and Medicaid Services, 2015). Those individual components include EMR/EHR, computerized provider order entry, electronic prescribing, electronic demographics, electronic clinical notes, and electronic problem lists. I created indicator variables for 4 levels of adoption: 1) All, 2) Part, 3) No Adoption, and 4)Unknown. Each component of HIT was assigned to one of these categories, after which categories 1 and 2 were combined to indicate at least partial adoption of the HIT-HIE component. I then combined all HIT-HIE elements into one category labeled “all measures” to denote EDs that have at least partial HIT adoption, consistent with meaningful use guidelines. Consistent with the literature, patient level covariates include race, gender and expected payer (Jha, 2010) (Selck & Decker, 2015). Hospital level controls include region, metropolitan statistical area, ownership, and whether or not there was an attending physician present at the time of visit.

Preliminary Statistics

I conducted various tests to determine correlations within the data. The first is a spearman's correlation matrix showing the relationships among all of the HIT factors. Unsurprisingly, they are all statistically significant and positively correlated with one another (e.g. having a high score on Electronic Clinical Documentation HIT on average means that the hospital will also have a high score on the other HITs). Interestingly,Spearman the total number of beds (log transformed to make the distribution more normally distributed) is statistically significantly related to all of the HIT factors, but it is a *negative* relationship with all of them. This means that hospitals that have *more* beds (thus larger patient population) are more likely to have *lower* scores on HIT factors. I found it interesting that larger hospitals have lower HIT scores because it seems that larger hospitals are the ones that would benefit from information technology implementation the most because they have more information to keep track of, whereas smaller hospitals don't have as much information to keep track of, but they use HIT implementation more. As a side note, Spearman's correlation is a non-parametric correlation analysis. It was necessary to use this instead of a more traditional, parametric Pearson's correlation because most of the distributions for the HIT factors were not normally distributed.

The second analysis I did was a series of ANOVAs comparing average HIT scores (for all 6) across different Control/Ownership types of hospitals. The original Ownership variable had about 20 categories nested under 4 main categories: Privately Owned, Non-profit, Federal

Government, and Non-Federal government. I had to collapse the two government categories into 1 because there weren't that many of them; therefore, there are just 3 categories. For all 6 HIT factors, Privately owned hospitals had higher HIT implementation, which isn't that surprising, but there are other things to consider to get a more nuanced discussion from the results. For example, the HIT categories where there is the largest difference in HIT implementation between Private hospitals and Non-profit or Government hospitals was in either Electronic Clinical Documentation, Computerized Provider Order Entry, and Decision Support. However, though Private hospitals scored higher on both Public Health Reporting and Medication Management, it was not actually that much higher. The difference is statistically significant, but possibly not all that much different in practice. The overall takeaway, though, is that in order from highest HIT implementation to lowest, the order is Privately owned, Government owned, then Non-profit.

D. Empirical Strategy

This study uses ordinary least squares (OLS) regression, logistic regression, and negative binomial regression to assess the effects of measures of HIT-HIE on specific health care delivery outcomes, and on emergency department quality indicators. The models control for observable patient demographics of age and race, along with total hospital bed and hospital ownership, in addition to metropolitan statistical area and payer for the NHAMCS set. I also control for potentially confounding unobserved time-invariant system characteristics, and system specific linear time trends.

Base Model

I modeled seven outcomes:

Equation 1:

log������a���������������

$$= �_0 + �_1 X_{���} + �_2 X_{����} + �_3 X_{��} + �_4 X_{MM} + �_5 X_{�����} + �_6 X_{���} + �_7 X_{��}$$

$$+ �_8 X_{���} + �_8 X_{���} + �_i X_c \ . + \in$$

Equation 2:

log������30 �a� ��a���i���

$$= �_0 + �_1 X_{���} + �_2 X_{����} + �_3 X_{��} + �_4 X_{MM} + �_5 X_{�����} + �_6 X_{���} + �_7 X_{��}$$

$$+ �_8 X_{���} + �_8 X_{���} + �_i X_c \ . + \in$$

Equation 3:

���ia��������h ����a�

$$= �_0 + �_1 X_{���} + �_2 X_{����} + �_3 X_{��} + �_4 X_{MM} + �_5 X_{�����} + �_6 X_{���} + �_7 X_{��}$$

$$+ �_8 X_{���} + �_8 X_{���} + �_i X_c \ . + \in$$

Equation 4:

���ia�������

$$= �_0 + �_1 X_{���} + �_2 X_{����} + �_3 X_{��} + �_4 X_{MM} + �_5 X_{�����} + �_6 X_{���} + �_7 X_{��}$$

$$+ �_8 X_{���} + �_8 X_{���} + �_i X_c \ . + \in$$

Equation 5:

ED length of visit, length of stay and physician wait time as HIT

$$= �_0 + �_1 ��T_{et} + �_2 X_{c��iet} + �_e + �_{it}$$

In the first model, adverse drug event is my outcome variable. The betas are the coefficients of the HIT-HIE variables as defined. The covariates consist of hospital and patient characterstics that include hospital ownership type, bed total, race, age and sex. Each model has the same format. To assess the effects of HIT-HIE on hospital readmissions, I employ a multiple logistic regression modelling technique with measures of HIT as the independent variables, and hospital readmission within 30 days as the dependent variable.

To assess the impact of HIT-HIE on ED measures of quality, I limited my analysis to the years 2007 and 2010 due to the high volume of missing responses in earlier years of the data. I employ an OLS multivariate regression to analyze length of visit, length of hospital stay and waiting times to see a physician. Length of visit is different from length of hospital stay in that length of visit is defined as the length of stay in the ED, whereas length of stay is the length of stay in the hospital after discharge from the ED to the hospital. These are both measured in minutes. I also used ED fixed effects, and lagged adoption model to account for acclimation. Y is the outcome of interest for visit i at time t . Other covariates included previously mentioned hospital level controls and patient level controls. I ran two regressions. The first regression tests the model for EDs with at least partial measures of HIT on the three measures of efficiency. The second regression tests the model for EDs with no measures of HIT-HIE. My decision to include this data source in the overall analysis is the nationally representative data across the US, it's high response rate, and the fact that it complements the inpatient and outpatient data from CMS with HIT-HIE impact on Emergency Departments.

In the next chapter, I discuss the results of preliminary and primary analyses, along with discussion and interpretation of the findings.

IV. RESULTS

A. Results Overview

This quantitative study was conducted to explore evidence for the relationship between different types and levels of HIT-HIE implementation and key healthcare outcomes. Specifically, six continuous variables representing HIT-HIE were constructed using the validated American Hospital Association's (AHA) HIT instrument. The six HIT instruments include level of implementation for electronic clinical documentation (ECD), computerized provider order entry(CPOE), clinical decision support(CDS), medication management(MM), discharge instructions and care summary documents(DICSD), and public health reporting(PHR). There were also three categorical measures of HIT-HIE implementation taken from the AHA survey. The three categorical HIT-HIE measures used were health information exchange functionalities, regional health information exchanges (HIE) participation, and clinical summary care records (CCD). The continuous healthcare outcomes of interest used for this study were length of stay and total charges accrued by the patient per hospital stay; the dichotomous healthcare outcomes used for the analysis were patient experience of an adverse drug event and patient readmission into the hospital within 30 days. For the NHAMCS dataset, the measures of HIT-HIE were electronic medical record(EMR), computerized provider order entry(CPOE), and electronic presecribing, and the outcomes of interest were length of visit, length of stay in the hospital, and wait time to see a physician. Chapter IV reveals the results of statistical analyses described in the research design presented in Chapter III. The following research hypotheses drive this study:

H_1: HIT-HIE as defined within this study contribute to increased and enhanced coordination of care amongst health care providers by providing critical information at the point of care. This may contribute to a reduction in adverse drug events.

H_2: HIT-HIE improves clinical quality metrics at the hospital level due to increased coordination of care across disparate entities, and improved health data collection, aggregation and dissemination, and may contribute to the reduction of hospital readmissions, and reduction of hospital length of stay.

H_3: HIT-HIE may affect hospital costs and expenditures. Initial start-up costs may be very high at the outset. However, in the intermediate to long run, hospitals may see lower costs as a result of increased efficiency in the healthcare delivery process.

H_4: HIT-HIEmay be particularly impactful in emergency department due to the unique constraints and processes. The necessity for timely clinical information on hand may improve emergency department efficiency metrics, such as shorter waiting time to see a physician, etc.

This chapter begins with a description of the sample using frequencies and measures of central tendency for all variables included in the analyses. The description of the sample is followed by a preliminary analysis section of bivariate analyses that were conducted to explore relationships within the data and provide guidance on the justification for including demographics as covariates in the primary models. Some categorical variables were recoded to correct for relatively low frequencies in some categories, and some continuous variables were log-transformed to correct for skewness. Next, the primary analyses that were used to investigate the propositions are reported using four multivariate modeling methods: ordinary least squares (OLS) regression, negative binomial regression, logistic regression, and rare events logistic regression.

The CMS data was accessed through the Chronic Conditions Data Warehouse (CCDW) enclave portal (https://www.ccwdata.org). This data source provided a robust patient population with conditions that could potentially benefit from improved care coordination. The original data file contained over 20 million observations; therefore, to reduce the computation time to a manageable amount, a random sample without replacement of 100,000 observations was taken from the data for analysis. The alpha level was set at .05, therefore, variables with *p* values < .05 are interpreted as significant and *p* values between .05 and .10 are occasionally discussed as marginally significant; however, due to the increased likelihood of Type I errors as a result of the large sample size, the a priori decision was made to only discuss significant relationships in logistic and negative binomial models with odds ratios (*OR*) below .9 or above 1.1. For OLS multiple regression, the cutoff for meaningful effect size is *Beta* larger than positive or negative .1. SAS Version 5.1 was used for the analyses. The NHAMCS is publicly available data access at http://www.cdc.gov/nchs/ahcd/ahcd_questionnaires.htm. The years 2002 to 2010 were used for this study. The alpha level was set at .05, therefore variables with *p* values <.05 were considered significant. SAS Version 9.4 was used for the analyses. The chapter closes with a summary and discussion of the results.

B. Sample Descriptives

Frequencies and percentages for the categorical descriptive variables are displayed in Table 1. The majority of hospitals had patients who had not experienced an adverse drug event

(99.9%) and had not been readmitted within 30 days (75.9%). In addition, the majority of hospitals reported that an arrangement existed to share electronic patient-level clinical data (82.7%), patients had participated or actively exchanged data (53.6%), and patients had access to their clinical summary care records (87.4%). The majority of hospitals had female (55.3%) and white (81.6%) patients. Finally, the majority of hospitals were owned by nonprofit organizations (81.1%).

Means and standard deviations for the continuous descriptive variables are displayed in Table II. Patient length of stay ranged from 1 to 331 days (*M* = 6.10, *SD* = 6.65). Due to a non-normal distribution, the variable was log-transformed and the length of stay ranged from 0 to 5.80 days (*M* = 1.46, *SD* = .82). Patient total charges ranged from $265 to $3,442,291 (*M* = 39,426.70, *SD* = 60,513.09). The variable was also log-transformed due to a non-normal distribution and total charges ranged from $5.58 to $15.05 (*M* = 10.09, *SD* = .94). Higher HIT scores were representative of lower levels of implementation based on the scale provided in the AHA dataset, where scores ranged from 1-fully implemented to 6-no implementation. Hospital scores on electronic clinical documentation scale ranged from 1 to 42 (*M* = 6.10, *SD* = 6.65), scores on computerized provider order entry ranged from 2 to 30 (*M* = 6.83, *SD* = 3.77), and scores on decision support ranged from 2 to 36 (*M* = 8.09, *SD* = 3.97). In addition, hospital scores on medication management ranged from 1 to 10 (*M* = 5.39, *SD* = .79), scores on discharge instructions and care summary documents ranged from 1 to 12 (*M* = 6.76, *SD* = 1.53), and scores on public health reporting ranged from 1 to 6 (*M* = 3.62, *SD* = 1.05). Finally, patient age ranged from 2 to 111 (*M* = 76.65, *SD* = 11.76) and the number of total beds ranged from 2 to 2249 (*M* = 410.63, *SD* = 331.24).

TABLE I

FREQUENCIES AND PERCENTAGES FOR CATEGORICAL VARIABLES

	n	%
Adverse Drug Event		
No Adverse Drug Event	99,926	99.9
Adverse Drug Event	74	.1
Readmission Within 30 Days		
Not Readmitted Within 30 Days	75,859	75.9
Readmitted Within 30 Days	24,140	24.1
Health Information Exchange Functionalities		
Arrangement Exists	79,654	82.7
Arrangement Does Not Exist	16,682	17.3
Regional HIE Participation		
Participating or Actively Exchanging Data	50,886	53.6
Have Framework to Participate but no Participation	35,840	37.7
No Framework and no Participation	8,230	8.7
Clinical Summary Care Records		
Yes	82,674	87.4
No	11,958	12.6
Gender		
Female	55,261	55.3
Male	44,738	44.7
Race		
Unknown	120	.1
White	81,591	81.6
Black	15,176	15.2
Other	792	.8
Asian	531	.5
Hispanic	1,472	1.5
North American Native	317	.3
Ownership Type		
Government	10,817	10.8
Nonprofit	81,076	81.1
Private	8,107	8.1

Note. Frequencies not summing to N = 100,000 and percentages not summing to 100 reflect missing data.

TABLE II

MEANS AND STANDARD DEVIATIONS FOR CONTINUOUS VARIABLES

	N	*M*	*SD*	Min	Max
Length of Stay	99,999	6.10	6.65	1.00	331.00
Length of Stay (Log-Transformed)	99,999	1.46	.82	.00	5.80
Total Charges	99,999	39,426.70	60,513.09	265.00	3,442,291.00
Total Charges (Log-Transformed)	99,999	10.09	.94	5.58	15.05
Electronic Clinical Documentation	100,000	9.40	3.93	1.00	42.00
Computerized Provider Order Entry	99,667	6.83	3.77	2.00	30.00
Decision Support	99,732	8.09	3.97	2.00	36.00
Medication Management	99,815	5.39	.79	1.00	10.00
Discharge Instructions and Care Summary Documents	99,796	6.76	1.53	1.00	12.00
Public Health Reporting	98,444	3.62	1.05	1.00	6.00
Patient Age	99,999	76.65	11.76	2.00	111.00
Total Beds	100,000	410.63	331.24	2.00	2,249.00

Note. *N* not equal to 100,000 reflect missing data.

C. Preliminary Analysis

A one-way analysis of variance (ANOVA) test was conducted to determine if the number of total beds differed by regional HIE participation. As shown in Table III, results revealed a significant relationship, *F* (2) = 1470.29, *p* < .001. Tukey's post hoc analyses revealed that hospitals at which participants participated in HIE or actively exchanged data had a significantly greater number of total beds (*M* = 469.97, *SD* = 380.96) than did hospitals that had a framework but no participation (*M* = 353.54, *SD* = 227.71) and hospitals with no framework and no participation (*M* = 357.06, *SD* = 351.25).

TABLE III

MEANS AND STANDARD DEVIATIONS FOR BED TOTAL BY REGIONAL HIE PARTICIPATION

	n	*M*	*SD*	*F*	*p*
Regional HIE Participation				1,470.29	< .001
Participating or Actively Exchanging Data	50,886	469.97 [a]	380.06		
Have Framework to Participate but no Participation	35,840	353.54 [b]	227.71		
No Framework and no Participation	8,230	357.06 [b]	351.25		

Note. Means with different superscripts differ significantly, *p* < .05.

Several ANOVA's were conducted to determine if the number of total beds and scores on electronic clinical documentation, computerized provider order entry, decision support, medication management, and discharge instructions and care summary documents differed by ownership type. As shown in Table IV, there was a significant relationship between ownership type and number of total beds, F (2) = 673.41, $p < .001$. Tukey's post hoc analyses revealed that all groups differed significantly with hospitals owned by nonprofit organizations having a greater number of total beds (M = 425.43, SD = 332.79) than did hospitals owned by the government (M = 392.54, SD = 338.65) and private companies (M = 286.70, SD = 273.54). There was also a significant relationship between ownership type and electronic clinical documentation scores, F (2) = 1035.12, $p < .001$. Tukey's post hoc analyses revealed that all groups differed significantly; private hospitals had significantly higher electronic clinical documentation scores (M = 11.27, SD = 6.22) than did hospitals owned by the nonprofit hospitals (M = 9.26, SD = 3.68), and non-profit hospitals had higher scores than government (M = 9.01, SD = 3.08) and. Results revealed a significant relationship between ownership type and computerized provider order entry scores, F (2) = 3,184.91, $p < .001$. Tukey's post hoc analyses showed that all groups differed significantly; hospitals owned by private companies had significantly higher computerized provider order entry scores (M = 9.93, SD = 5.77) than did hospitals owned by the government (M = 6.77, SD = 3.13) and nonprofit organizations (M = 6.53, SD = 3.44). Furthermore, the results showed a significant relationship between ownership type and decision support scores, F (2) = 3,191.40, $p < .001$. Tukey's post hoc analyses revealed that all groups differed significantly; hospitals owned by private companies had significantly higher decision support scores (M = 11.36, SD = 6.17) than did hospitals owned by the government (M = 7.91, SD = 3.58) and nonprofit organizations (M = 7.79, SD = 3.57). There was also a significant relationship between ownership type and medication management scores, F (2) = 896.9, $p < .001$. Tukey's post hoc analyses revealed that all groups differed significantly; hospitals owned by private companies had significantly higher medication management scores (M = 5.72, SD =

1.17) than did hospitals owned by the government (*M* = 5.26, *SD* = .68) and nonprofit organizations (*M* = 5.37, *SD* = .75). Finally, results revealed a significant relationship between ownership type and discharge instructions and care summary document scores, F (2) = 340.26, $p < .001$. Tukey's post hoc analyses revealed that all groups differed significantly; hospitals owned by private companies had significantly higher discharge instructions and care summary documents scores (*M* = 7.17, *SD* = 2.14) than did hospitals owned by the government (*M* = 6.85, *SD* = 1.35) and nonprofit organizations (*M* = 6.71, *SD* = 1.47).

Pearson's product–moment correlations were conducted to examine the relationship between HIT scores and the total number of beds. As shown in Table V, the total number of beds was negatively correlated with all HIT scores, *p*s < .001. Fewer numbers of beds were associated with higher HIT scores (*r*s ranging from -.04 to -.21). In addition, all HIT scores were positively correlated with each other, *p*s < .001. Higher scores on one scale were associated with higher scores on the other scales (*r*s ranging from .23 to .63). Furthermore, discharge instructions and care summary documents had the weakest relationship with bed count, while decision support had the strongest relationship with bed count.

TABLE IV

MEANS AND STANDARD DEVIATIONS FOR BED TOTAL AND HIT SCALES BY HOSPITAL OWNERSHIP TYPE

	N	*M*	*SD*	*F*	*p*
Bed Total				673.41	< .001
Government	10,817	392.54 [a]	338.65		
Nonprofit	81,076	425.43 [b]	332.79		
Private	8,107	286.70 [c]	273.54		
Electronic Clinical Documentation				1,035.12	< .001
Government	10,817	9.01 [a]	3.08		
Nonprofit	81,076	9.26 [b]	3.68		
Private	8,107	11.27 [c]	6.22		
Computerized Provider Order Entry				3,184.91	< .001
Government	10,786	6.77 [a]	3.13		
Nonprofit	80,774	6.53 [b]	3.44		
Private	8,107	9.93 [c]	5.77		
Decision Support				3,191.40	< .001
Government	10,803	7.91 [a]	3.58		
Nonprofit	80,837	7.79 [b]	3.57		
Private	8,092	11.36 [c]	6.17		
Medication Management				896.90	< .001
Government	10,811	5.26 [a]	.68		
Nonprofit	80,925	5.37 [b]	.75		
Private	8,079	5.72 [c]	1.17		
Discharge Instructions and Care Summary Documents				340.26	< .001
Government	10,802	6.85 [a]	1.35		
Nonprofit	80,945	6.71 [b]	1.47		
Private	8,049	7.17 [c]	2.14		

Note. Means with different superscripts differ significantly, $p < .05$.

TABLE V

PEARSON'S PRODUCT MOMENT CORRELATION AMONG HIT SCALES AND BED TOTAL

	1	2	3	4	5	6
1. Total Beds						
2. Electronic Clinical Documentation	-.170***					
3. Computerized Provider Order Entry	-.211***	.626***				
4. Decision Support	-.213***	.569***	.594***			
5. Medication Management	-.070***	.316***	.267***	.296***		
6. Discharge Instructions and Care Summary Documents	-.041***	.283***	.211***	.298***	.440***	
7. Public Health Reporting	-.105***	.225***	.226***	.240***	.296***	.382***

Note. **p* < .05, ***p* < .01, ****p* < .001.

Several independent samples *t* tests were conducted to compare average age, number of beds, and HIT scores of hospitals with patients who were readmitted within 30 days to hospitals with patients who were not readmitted within 30 days. As shown in Table VI, patients who were not readmitted within 30 days were significantly older (M = 77.02, SD = 11.60) than were patients who were readmitted within 30 days (M = 75.48, SD = 12.18), t (39,046) = 17.27, p < .001. Also, hospitals with patients who were readmitted within 30 days had a significantly greater number of beds (M = 418.50, SD = 335.90) than did hospitals with patients who were not readmitted within 30 days (M = 408.10, SD = 329.70), t (40,010) = -4.20, p < .001. Furthermore, hospitals with patients who were readmitted within 30 days had significantly higher electronic clinical documentation scores (*M* = 9.56, *SD* = 4.40) than did hospitals with patients who were not readmitted within 30 days (*M* = 9.35, *SD* = 3.77), *t* (36,128) = -6.95, *p* < .001, and hospitals with patients who were readmitted within 30 days had significantly higher computerized provider order entry scores (*M* = 6.96, *SD* = 4.05) than did hospitals with patients who were not readmitted within 30 days (*M* = 6.79, *SD* = 3.68), *t* (37,490) = -5.85, *p* < .001. Furthermore, the results showed that hospitals with patients who were readmitted within 30 days had significantly higher decision support scores (*M* = 8.21, *SD* = 4.27) than did hospital with patients who were not readmitted within 30 days (*M* = 8.05, *SD* = 3.86), *t* (37,386) = -5.07, *p* < .001. Additionally, hospitals with patients who were readmitted within 30 days had significantly higher medication management scores (*M* = 5.42, *SD* = .84) than did hospitals with patients who were not readmitted within 30 days (*M* = 5.38, *SD* = .78), *t* (37,837) = -5.73, *p* < .001. Results revealed that hospitals with patients who were readmitted within 30 days had significantly higher discharge instructions and care summary documents scores (*M* = 6.80, *SD* = 1.58) than did hospitals with patients who were not readmitted within 30 days (*M* = 6.75, *SD* = 1.51), *t* (39,144) = -4.15, *p* < .001. Finally, results revealed that hospitals with patients who were readmitted within 30 days had significantly higher public health reporting scores (*M* = 3.63, *SD* = 1.07) than hospitals with patients who were not readmitted within 30 days (*M* = 3.61, *SD* = 1.04), *t* (39,063) = -2.20, *p* = .028. These unexpected results may be a result of enhanced tracking of these quality metrics made possible by the implementation of HIT-HIE measures.

TABLE VI

MEANS AND STANDARD DEVIATIONS FOR AGE, BED TOTAL, AND HIT SCALES BY 30-DAY READMISSION

	n	*M*	*SD*	*t*	*p*
Age				17.27	< .001
Not Readmitted Within 30 Days	75,859	77.02	11.60		
Readmitted Within 30 Days	24,140	75.48	12.18		
Bed Total				4.20	< .001
Not Readmitted Within 30 Days	75,859	408.10	329.70		
Readmitted Within 30 Days	24,140	418.50	335.90		
Electronic Clinical Documentation				6.95	< .001
Not Readmitted Within 30 Days	75,859	9.35	3.77		
Readmitted Within 30 Days	24,140	9.56	4.40		
Computerized Provider Order Entry				5.85	< .001
Not Readmitted Within 30 Days	75,600	6.79	3.68		
Readmitted Within 30 Days	24,066	6.96	4.05		
Decision Support				5.07	< .001
Not Readmitted Within 30 Days	75,664	8.05	3.86		
Readmitted Within 30 Days	24,067	8.21	4.27		
Medication Management				5.73	< .001
Not Readmitted Within 30 Days	75,729	5.38	.78		
Readmitted Within 30 Days	24,085	5.42	.84		
Discharge Instructions And Care Summary Documents				4.15	< .001
Not Readmitted Within 30 Days	75,725	6.75	1.51		
Readmitted Within 30 Days	24,070	6.80	1.58		
Public Health Reporting				2.20	.028
Not Readmitted Within 30 Days	74,746	3.61	1.04		
Readmitted Within 30 Days	23,697	3.63	1.07		

Note. Ψ Equal variances not assumed statistics reported.

An independent samples *t* test was conducted to compare the mean bed totals of hospitals for patients who experienced an adverse drug event to the mean bed totals of hospitals for patients who had experienced an adverse drug event. Log transformation was performed in order to account for the small sample size. As shown in Table VI, results revealed that hospitals with patients who had not experienced adverse drug events had a significantly greater number of total beds (M = 410.70, SD = 331.30) than did hospitals with patients who had experienced an adverse drug event (M = 295.50, SD = 239.80), t (73.21) = 4.13, p < .001.

TABLE VII

MEANS AND STANDARD DEVIATIONS FOR BED TOTAL BY ADVERSE DRUG EVENT

	n	*M*	*SD*	*t*	*p*
Bed Total				4.13	< .001
No Adverse Drug Event	99,926	410.70	331.30		
Adverse Drug Event	74	295.50	239.80		

Note. Ψ Equal variances not assumed statistics reported.

A one-way ANOVA was conducted to determine if length of stay differed by regional HIE participation. As shown in Table VIII, results revealed a significant relationship, F (2) = 9.08, p < .001. Tukey's post hoc analyses revealed that hospitals with the framework to participate but no participation had patients who spent significantly less time in the hospital (M =

1.45, *SD* = .85) than did hospitals participating or actively exchanging data (*M* = 1.47, *SD* = .82) and hospitals with no framework and no participation (*M* = 1.48, *SD* = .85).

TABLE VIII

MEANS AND STANDARD DEVIATIONS FOR LENGTH OF STAY BY REGIONAL HIE PARTICIPATION

	n	*M*	*SD*	*F*	*p*
Regional HIE Participation				9.08	< .001
Participating or Actively Exchanging Data	50,886	1.47 [a]	.82		
Have Framework to Participate but no Participation	35,840	1.45 [b]	.80		
No Framework and no Participation	8,230	1.48 [a]	.85		

Note. Means with different superscripts differ significantly, $p < .05$.

NHAMCS Sample Description

Frequencies and percentages for the categorical sample descriptions are found in table 9 below. 4% of hospitals participating in the survey had all measures of EMR listed on the questionnaire, while 8% had partial EMR, and the majority did not enter a response for EMR (68%). 15% of hospitals had all or partial CPOE, while 15% of hospitals had all or partial electronic prescribing. The majority of hospitals had female (54%) and White patients (65%). The majority of hospitals were governmemnt owned (24%), and were not in metropolitan statistical areas (30%).

TABLE IX

FREQUENCIES AND PERCENTAGES FOR CATEGORICAL VARIABLES

	n	%
EMR		
No Response	30,377	73.8
All EMR	1,766	4.3
Partial EMR	3,652	8.9
No EMR	1,458	3.5
Unknown EMR	3,888	9.5
CPOE		
No Response	30,092	73.1
All CPOE	4,458	10.8
Partial CPOE	2,362	5.7
No CPOE	25	.1
Unknown CPOE	4,204	10.2
CTOE (Computerized Test Order Entry)		
No Response	30,377	73.8
All CTOE	5,925	14.4
Partial CTOE	870	2.1
No CTOE	4	.0
Unknown CTOE	3,965	9.6
Electronic Demographics		
No Response	30,385	73.9
All Electronic Demographics	6,476	15.7
Partial Electronic Demographics	336	.8
No Electronic Demographics	3,944	9.6
Electronic Prescribing		
No Response	32,875	79.9
All ePrescribing	1,513	3.7
Partial ePrescribing	2,549	6.2
No ePrescribing	4,204	10.2
Electronic Problem List		
No Response	30,500	74.1
All Problem List	3,999	9.7
Partial Problem List	1,908	4.6
Unknown	4,734	11.5

TABLE IX continued

FREQUENCIES AND PERCENTAGES FOR CATEGORICAL VARIABLES

	n	%
Electronic Notes		
No Response	10,217	24.8
All Notes	19,849	48.3
Partia Notes	4,893	11.9
Unknown	6,182	15.0
All Measures		
0	6,898	16.8
1	18,094	44.0
2	16,149	39.3
Owner		
Blank	30,389	73.9
Non Profit	8,220	20.0
Governmemt	1,719	4.2
Proprietary	813	2.0
MSA		
0	30,828	74.9
MSA	10,252	24.9
Non MSA	61	.2
Region		
Blank	29,510	72.4
Northeast	3,338	8.1
Midwest	2,573	6.3
South	3,578	8.7
West	2,142	5.2
Gender		
Female	22,459	54.6
Male	18,682	45.4

TABLE IX continued

FREQUENCIES AND PERCENTAGES FOR CATEGORICAL VARIABLES

	n	%
Race		
White	26,674	64.8
Black	8,924	21.7
Asian	1,046	2.5
Hispanic	255	.6
American Indian/Alaska Native	199	.5
Multuracial	293	.7
Unknown	3,750	9.1
Payer		
Medicare	10,891	26.5
Self-Pay	3,586	8.7
Medicaid	11,351	27.6

Means and standard deviations for continuous descriptive variables are found in Table X. The mean length of visit is 254 minutes, with a minimum and maximum of 0 and 5610 minutes respectively. Mean length of stay in hospital was 99 days, with a minimum of 0 and maximum of 1110 days. The mean wait time to see a physician once admitted was 56 minutes, with minimum of 0 and maximum of 1397 minutes. Finally, mean age at visit was 42 years.

D. Primary Analysis

In this section, I analyze the impact of HIT/HIE on three measures of health care quality: adverse drug events, 30-day hospital readmissions, and length of stay. I also analyze the impact of HIT/HIE on measures of cost. Adverse drug events may include accidental drug poisoning, dosage failures, or other unintended reactions to drugs as prescribed. As stated in Hypothesis 1, components of HIT such as drug alerts, medication management and allergy flags could reduce the incidence of adverse drug events.

TABLE X

MEANS AND STANDARD DEVIATIONS FOR CONTINUOUS VARIABLES

	N	*M*	*SD*	Min	Max
Length of Visit (minutes)	41,141	254.77	278.17	0	5,610
Length of Stay (minutes)	41,141	99.17	297.55	0	1,110
Physician Wait Time (minutes)	41,141	56.12	81.85	0	1,397
Age	41,141	41.77	25.32	0	100

Table IX presents the results of a rare events logistic regression predicting adverse drug event using all nine measures of HIT implementation, as well as the covariates race (White is the reference category in all primary models), gender (female is the reference category in all primary models), patient age, total number of beds in the hospital, and hospital ownership type (private ownership is the reference category in all primary models). A rare events logistic regression was chosen in lieu of a standard logistic regression due to the relatively low frequency of events (see Table I). Overall, the model was only marginally significant, χ^2 (18) = 28.46, p = .055, Nagelkerke R^2 = .034. Of all the HIT variables, only clinical decision support (CDS) (*OR* = .883, p = .013) and discharge instructions and care summary documents (DISCD; *OR* = 1.225, p = .036) were statistically significant predictors of adverse drug events. As mentioned previously, higher HIT scores indicate lower levels of implementation. These results indicate that as decision support implementation increased, the likelihood of adverse drug reactions also increased, and as the implementation of discharge instructions and care summary documents increased the likelihood of patients experiencing adverse drug events decreased. This could be as an artifact of increased tracking and measurement of adverse drug events made possible by teh electronic system. Among the covariates, only hospital ownership type was statistically significant. Specifically, nonprofit hospitals were more than twice as likely as privately owned hospitals to experience adverse drug events in their patients (*OR* = 2.372, $p = .022$).

Results of a logistic regression predicting readmission within 30 days is shown in Table XII. Hypothesis 2 conjectures that the elements of HIT in this study may lead to reduction in 30 day readmissions. Inadequate follow up, insufficient information at the point of care, and insufficient discharge information are all factors that contribute to readmissions within 30 days, thus lowering hospital quality. The overall model was statistically significant, χ^2 (18) = 435.76, $p < .001$, Nagelkerke $R^2 = .007$. Clinical summary care documentation was the only HIT variable that was statistically significant; however, the effect size (*OR* = .945, $p = .033$) did not surpass the previously stated cutoff to protect against false positives. Again, hospital ownership type was a statistically significant predictor. Government-owned hospitals were more likely than were privately owned hospitals to have patients readmitted within 30 days (OR = 1.126 , $p < .004$). Also, race was a statistically significant predictor of 30-day readmission. Both Black (*OR* = .835, $p < .001$) and Hispanic (*OR* = .842, $p = .007$) patients were less likely than were White patients to be readmitted within 30 days. No other covariates or HIT variables were significant predictors of 30-day readmission.

TABLE XI

SUMMARY OF MULTIPLE LOGISTIC REGRESSION ANALYSIS FOR PREDICTING ADVERSE DRUG EVENT

						95% CI	
	B	*SE*	*Wald*	*OR*	*p*	*LL*	*UL*
Race							
Black	-.220	.32	.48	.803	.491	.431	1.625
Hispanic	.674	1.35	.25	1.963	.617	.276	248.978
Asian	-.439	1.36	.10	.645	.747	.092	81.495
Other	-.790	.79	1.00	.454	.318	.122	4.023
Male	.450	.24	3.37	1.568	.066	.953	2.653
Patient Age	.010	.01	.85	1.010	.357	.988	1.033
Total Beds	-.002	.00	9.87	.998	.002	.997	.999
Electronic Clinical Documentation	.007	.04	.03	1.007	.872	.911	1.098
Computerized Provider Order Entry	.026	.04	.37	1.027	.542	.929	1.119
Decision Support	-.125	.05	6.12	.883	.013	.785	.978
Medication Management	.081	.16	.25	1.085	.618	.752	1.517
Discharge Instructions and Care Summary Documents	.203	.10	4.38	1.225	.036	.994	1.503
Public Health Reporting	-.045	.12	.13	.956	.717	.733	1.230
Health Information Exchange Functionalities	.098	.35	.08	1.103	.779	.542	2.351
Regional HIE Participation	.269	.21	1.63	1.309	.201	.834	2.013
Clinical Summary Care Records	.611	.43	2.06	1.843	.152	.797	5.004
Ownership							
Government	.498	.45	1.22	1.645	.270	.621	4.228
Nonprofit	.864	.38	5.26	2.372	.022	1.006	5.003

Note. χ^2 (18) = 28.46, $p < .055$, Nagelkerke $R^2 = .034$.

TABLE XII

SUMMARY OF MULTIPLE LOGISTIC REGRESSION ANALYSIS FOR PREDICTING READMISSION WITHIN 30 DAYS

	B	*SE*	*Wald*	*OR*	*p*	95% CI *LL*	95% CI *UL*
Race							
Black	-.180	.02	68.70	.835	< .001	.801	.872
Hispanic	-.172	.06	7.36	.842	.007	.743	.953
Asian	.073	.11	.44	1.075	.507	.868	1.332
Other	-.035	.07	.22	.966	.639	.837	1.116
Male	-.033	.02	4.20	.968	.040	.938	.999
Patient Age	-.010	.00	209.28	.990	< .001	.989	.992
Total Beds	.000	.00	18.27	1.000	< .001	1.000	1.000
Electronic Clinical Documentation	.004	.00	2.09	1.004	.149	.998	1.010
Computerized Provider Order Entry	.004	.00	1.64	1.004	.201	.998	1.010
Decision Support	-.005	.00	2.67	.995	.102	.990	1.001
Medication Management	.018	.01	2.13	1.018	.145	.994	1.043
Discharge Instructions and Care Summary Documents	-.004	.01	.39	.996	.534	.983	1.009
Public Health Reporting	.012	.01	1.97	1.012	.161	.995	1.030
Health Information Exchange Functionalities	.018	.03	.46	1.018	.499	.966	1.073
Regional HIE Participation	-.002	.02	.02	.998	.877	.967	1.029
Clinical Summary Care Records	-.057	.03	4.55	.945	.033	.897	.995
Ownership							
Government	.119	.04	8.51	1.126	.004	1.040	1.219
Nonprofit	.056	.03	2.65	1.058	.104	.989	1.132

Note. χ^2 (18) = 435.76, $p < .001$, Nagelkerke $R^2 = .007$.

Results of a negative binomial regression predicting length of stay (log-transformed) is displayed in Table XIII. Though log-transformations often transform skewed distributions into approximately normal distributions, length of stay remained highly skewed, therefore, the negative binomial model was applied instead of an OLS regression; however, OLS regression and Poisson regression were both used as sensitivity analyses and the substantive results were the same. Overall, the model was not statistically significant, χ^2 (18) = 40,930.85, p = .457. Also, none of the HIT variables and none of the covariates were statistically significant predictors of length of stay.

Finally, the results of an OLS regression predicting total charges are displayed in Table 14. Due to skewness, total charges was also log-transformed, and the resulting transformed variable was normally distributed; therefore, OLS regression was justified. The overall model was statistically significant, F (18, 89,677) = 299.91, p < .001, R^2 = .057. Again, none of the HIT variables were significant predictors of total charges, but hospital ownership was a significant predictor of total charges. Both government owned hospitals (*Beta* = -.169, p < .001) and nonprofit hospitals (*Beta* = -.139, p < .001) had lower total charges than privately owned hospitals, on average. Also, total number of beds (*Beta* = .195, p < .001) was a significant predictor of totals charges. As the number of beds in a hospital increases (i.e., larger hospitals) the total charges also increases. No other HIT variables or covariates were significantly related to total charges.

TABLE XIII

SUMMARY OF NEGATIVE BINOMIAL REGRESSION ANALYSIS FOR PREDICTING LENGTH OF STAY

						95% CI	
	B	*SE*	*Wald*	*irr*	*p*	*LL*	*UL*
Race							
Black	.033	.01	17.43	1.033	< .001	.017	.048
Hispanic	-.032	.02	1.84	.969	.175	-.078	.014
Asian	-.032	.04	.72	.968	.398	-.107	.043
Other	-.021	.03	.63	.979	.427	-.073	.031
Male	-.015	.01	7.54	.985	.006	-.026	-.004
Patient Age	.002	.00	50.91	1.002	< .001	.001	.002
Total Beds	.000	.00	126.20	1.000	< .001	.000	.000
Electronic Clinical Documentation	.003	.00	10.05	1.003	.002	.001	.005
Computerized Provider Order Entry	-.001	.00	.86	.999	.354	-.003	.001
Decision Support	.001	.00	.67	1.001	.413	-.001	.003
Medication Management	.005	.00	1.20	1.005	.274	-.004	.013
Discharge Instructions and Care Summary Documents	.002	.00	.63	1.002	.428	-.003	.006
Public Health Reporting	.000	.00	.00	1.000	.982	-.006	.006
Health Information Exchange Functionalities	.024	.01	6.73	1.025	.010	.006	.043
Regional HIE Participation	-.013	.01	5.27	.987	.022	-.024	-.002
Clinical Summary Care Records	.010	.01	1.04	1.010	.308	-.009	.028
Ownership							
Government	-.037	.01	6.69	.964	.010	-.065	-.009
Nonprofit	-.034	.01	7.71	.967	.006	-.058	-.010

Note. χ^2 (18) = 40,930.85, p = .457.

TABLE XIV

SUMMARY OF MULTIPLE REGRESSION ANALYSIS FOR PREDICTING COST

	Unstandardized B	*SE*	*Beta*	*t*	*p*
Race					
Black	.006	.01	.002	.67	.501
Hispanic	-.003	.03	< -.001	.12	.908
Asian	.134	.04	.011	3.24	.001
Other	-.005	.03	< -.001	.18	.859
Male	.071	.01	.038	11.51	< .001
Patient Age	-.003	.00	-.031	9.40	< .001
Total Beds	.001	.00	.195	57.31	< .001
Electronic Clinical Documentation	.007	.00	.027	6.32	< .001
Computerized Provider Order Entry	-.012	.00	.043	9.74	< .001
Decision Support	-.013	.00	.050	12.11	< .001
Medication Management	-.010	.00	.008	2.01	.045
Discharge Instructions and Care Summary Documents	.004	.00	.007	1.76	.079
Public Health Reporting	.012	.00	.013	3.49	.001
Health Information Exchange Functionalities	.041	.01	.016	3.96	< .001
Regional HIE Participation	.028	.01	.019	4.53	< .001
Clinical Summary Care Records	.033	.01	.012	3.20	.001
Ownership					
Government	-.508	.02	-.169	31.98	< .001
Nonprofit	-.346	.01	-.139	25.41	< .001

Note. F (18, 89,677) = 299.91, p < .001, R^2 = .057.

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Estimates were considered significant at p<.05. Standard errors were adjusted to account for the stratified cluster design of the sample. Previous literature looks at three mutually exclusive categories of adoption (Selck & Decker, 2015), and two thresholds of adoption (Desroches, et al., 2008). I combine all levels of adoption into partial and all adoption in order to isolate those EDs with at least partial components, comparing them to those EDs that have no components of HIT implemented. Table XV shows the results of a OLS multivariable analysis looking at effects of the previously defined HIT measures on ED length of visit, as well as the covariates race (White is the reference category in all models), gender(female is the reference category in all primary models), hospital ownership (non-profit is the reference category in all models), payor (medicaid is the reference category in all models), and metropolitan statistical area (Northeast region is the reference category in all models), and a categorical variable for whether or not there was an attending physician present. The overall model was statistically significant, *F* (<.001). All of the covariates were significant predictors of length of visit. I found that EDs with all or partial measures of HIT had ED visits that were 5 minutes shorter than those without measures of HIT(*Beta* =-5.17, *p*<.001), controlling for the previously mentioned covariates.

Whether or not an attending physician was present had the greatest effect on length of visit, with the presence of an attending physician accounting for 22 minutes shorter visits(*Beta*=-21.69, *p*<.001) than those without an attending physician present. Furthermore, non-profit hospitals experience 13 minutes shorter visits (*Beta*=.13.31, *p*<.001) compared to government and private hospitals. These findings were significant at the .05 per cent level (p<.001). Although weak, these results are consistent with the hypothesis 4, which states that measures of HIT such as EMR/EHR may enhance and speed up processes in the ED, thus reducing the length of visit. This may be particularly salient in the ED, where treatment is often times time-sensitive, and thus benefit most from electronic access to information.

TABLE XV

SUMMARY OF MULTIPLE REGRESSION ANALYSIS FOR PREDICTING LENGTH OF VISIT

	Beta	*SE*	*B*	*t*	*p*
Black	69.950	1.13	.090	62.19	< .001
Male	-3.160	1.37	-.010	2.32	.021
Region	69.950	.68	.080	102.16	< .001
Payer	14.310	1.26	.020	11.34	< .001
All Measures of HIT	-5.180	.38	-.010	13.49	< .001
Non-Profit	-13.310	.31	-.020	42.62	< .001
Attending Physician Present	-21.690	.95	-.030	22.88	< .001
Metropolitan Statistical Area	20.580	1.03	.030	20.07	< .001

Note. R^2 = .02, p < .001, "p < .001.

Table XVshows the results for effects of HIT on wait time to see a physician. The overall model was statistically significant, *F* (<.001). The results revealed that hospitals with at least partial measures of HIT experienced just over 1 minute shorter wait time *(Beta*=-1.14, *p*<.001) when controlling for the other covariates previously mentioned. The results are statistically significant at the .05 percent level. While statistically significant, the results are modest and may not be compelling in attemps to justify investments in HIT.

TABLE XVI

SUMMARY OF MULTIPLE REGRESSION ANALYSIS FOR PREDICTING PHYSICIAN WAIT TIME

Parameter	*Beta*	*SE*	*B*	*t*	*p*
Black	17.760	.24	.090	72.99	< .001
Male	-.670	.12	.000	5.32	< .001
Region	-.360	.12	.000	3.07	.002
Payer	2.540	.29	.010	8.87	< .001
All Measures of HIT	-1.140	.05	-.010	22.89	< .001
Non-Profit	2.000	.04	.010	45.44	< .001
Attending Physician Present	-12.040	.17	-.080	71.47	< .001
Metropolitan Statistical Area	5.620	.17	.040	32.45	< .001

Note. R^2 = .02, $p < .001$, "$p < .001$, with allmeasurescat as the measure of HIT in all subsequent tables.

Finally, Table XVII reveals the results of effects of HIT on length of stay in the hospital. The results revealed that hospitals with at least partial measures of HIT were responsible for a 15 minute increase in length of stay when controlling for the previously mentioned covariates (*Beta* = 15.374, $p < .001$). The overall model was statistically signficant. The result of HIT measures on length of stay run contrary to Hypothesis 4 and will be discussed further in the next section.

TABLE XVII

SUMMARY OF MULTIPLE REGRESSION ANALYSIS FOR PREDICTING LENGTH OF STAY

	Beta	*SE*	*B*	*t*	*p*
Black	10.140	.28	.010	36.05	< .001
Male	-1.820	.16	.000	11.35	< .001
Region	-49.470	.08	-.040	649.05	< .001
Payer	-8.580	.27	-.010	31.58	< .001
All Measures of HIT	15.370	.07	.030	235.34	< .001
Non-Profit	-183.510	.05	-.190	3456.29	< .001
Attending Physician Present	-694.890	.33	-.710	2106.35	< .001
Metropolitan Statistical Area	-107.160	.32	-.110	331.57	< .001

Note. R^2 = .02, p < .001, "p < .001.

E. Summary/Discussion

The federal government has allocated approximately $20 billion to facilitate the adoption and implementation of HIT with the expectation that this technology will ultimately improve the overall quality and efficiency of care and overall health care delivery, while reducing costs. This rationale formed the premise for the hypotheses in this study:

Hypothesis 1 states that HIT-HIE may lead to reductions in adverse drug events, and may also increase the amount of information available to care providers. When looking at the outcome adverse drug event, only two out of the nine measures of HIT-HIE were found to be significantly related to adverse drug events. More specifically, discharge instructions and care summary documentation, along with clinical decision support systems were found to be significant predictors of adverse drug events. None of the other measures of HIT-HIE were significantly related to adverse drug outcomes. Earlier in this paper, I discussed discharge instructions and care summary documentation and clinical decision support as two measures of HIT that are integral to care coordination across disparate departments and health systems. Discharge instructions and care summary documentation allows providers at disparate hospitals to obtain the medical history and summary for patients, regardless of medical home, and is critical for transitional care. Furthermore, it facilitates timely access to patient information (Kripalani , et al., 2007). Clinical decision support systems help facilitate improved provider decision-making. Access to patient medication history can mitigate risks associated with prescription of drugs for which the patient may be allergic, or other medication contraindications. The Institute of Medicine suggests that decision support systems and other measures of HIT-HIE, coupled with establishment of uniform data standards could hep reduce the incidence of medication errors and reduce the incidence of preventable adverse drug events (Aspden, Wolcott, Bootman, & Cronenwett, 2007). Discharge instructions provide the patient as well as providers at different institutions access to more information about the patient, and can thus help facilitate more informed medical decisions. This study indicates that as CDISC implementation increases, adverse drug events decrease. The results of this study also revealed that adverse events actually increase with increased CDS implementation. This suggests that HIT-HIE is not associated with a reduction in adverse drug events. Agha (2011) found similar results when looking at adverse drug events and HIT-HIE. However, Evans, et al., reported opposite outcomes (Evans, Pestotnik, Classen, & Burke, 1999) (Evans, et al., 1998).

This counterintuitive outcome is telling. Clinical Decision Support Systems allow providers to make more timely, informed decisions about a patient's care. The information provided in CDSS may reveal *more* adverse drug events simply by virtue of having the critical patient information, including medication history on hand. This finding supports the fact that use of CDSS provides more information at the point of care, thus identifying more adverse drug events than that which would be identified in the absence of such systems. The other measures of HIT-HIE did not provide support for reduction of adverse drug events. This null finding is explained later in ths paper.

Furthermore, looking at 30 day hospital readmissions, CCD was found to be the only statistically significant measure of HIT. This result weakly supports hypotheses 2, in that CCD facilitates care coordination both within hospitals and between disparate points of care and improves clinical quality metrics, one of which is 30 day hospital readmissions. Furthermore, the information obtained from CCD among different providers may provide more information that could be instrumental in enhancing the care of the patient, thus limiting unnecessary hospital readmissions. I consider these results suggestive evidence due to low effect size. However, the literature supports the fact that CCD can serve as a form of transitional care, which studies have shown can reduce hospital and emergency department readmissions (Rennke, et al., 2013), (Maxson, Jain, & McKethan, 2010). Continuity of Care Documentation can also be considered a "bridging strategy" to prevent adverse outcomes after discharge. Reduced hospital readmissions are an expected outcome of improved care coordination as a result of the use of CCD. The remaining HIT variables were not significant predictors of 30 day hospital readmissions. These results are similar to results obtained by Desroches et al., which found no association between

HIT adoption and hospital readmission rates (DesRoches, Campbell, & Vogeli, 2010).

Furthermore, none of the HIT-HIE variables were statiscally related to length of stay. This hypothesis was based on the assumption that reductions in length of stay would occur as a consequence of quicker patient processing time, such as administering medications, ordering tests and procedures, and collecting important information as a result of having information on hand. This null finding may be indicative of the fact that length of stay has been on a steady decline since the 1980s, and the incentives to reduce length of stay may not be as evident to hospitals (Statistics, 2007). This finding, while null, is supported by recent works looking at the impact of different forms of HIT-HIE on length of stay and other measures. Thompson et al. Conducted a study on the impact of EMR on length of stay and other measures, and concluded that electronic interventions did not appear to have a significant or substantial impact on length of stay (Thompson, O'Horo, Pickering, & Herasevich, 2015). Furthermore, results of several systematic reviews have not found significant effects of HIT-HIE on length of stay, which highlights the fact that additional research is needed to generate evidence to support effects of HIT-HIE on length of stay (Thompson, O'Horo, Pickering, & Herasevich, 2015).

Additionally, when looking at Hypothesis 3, although the model is statistically significant, none of the HIT-HIE measures were found to be statistically related to hospital cost. One reason for this null finding could be that, given the fairly recent implementation of HIT at most hospitals, the charges have not yet reflected investments in HIT-HIE. Furthermore, with the monetary incentivization of EHR/EMR as part of meaningful use, the costs of HIT-HIE may have been cancelled out, or may not yet be evident. Costs for this study were determined using administrative claims data from Medicare patients, and as such, are generally considered the best available measure of inpatient costs. However, the data may not represent the costs for patients under the age of sixty-five.

The NHAMCS results for outcome efficiency measures length of visit and wait time to see a physician weakly support previous research that indicates that measures of HIT-HIE improve care coordination and result in better process outcomes, particularly for length of hospital visit, average length of stay, and physician wait times. Contrasted with the AHA study, HIT-HIE seems to have some benefits unique to the ED, which may not yet be realized in general physician's offices, or hospital-wide studies to date (Stokes-Buzzelli, Peltzer-Jones, Martin, Ford, & Weise, 2010), (New England Healthcare Institute, 2010). The very nature of emergency departments necessitates quick decision-making at the point of care. Lack of critical patient information can result in increased medical errors and increased processing and administrative time, along with redundant imaging and tests. Furthermore, patients that present at emergency departments may not necessarily obtain regular care in that particular health system, and medical history, medication history and other pieces of information may not be readily available to the provider in the absence of electronic records. Scholars at the University of Michigan conducted a study in which the exchange of clinical information through HIE in emergency departments suggested fewer repeated medical scans (Lammers, Adler-Milstein, & Kocher, 2014). Taken together studies suggest that HIT-HIE may increase efficiency in EDs. The results of this study have shown that access to information may suggest a mildly positive effect on the two quality outcomes specifically for emergency departments- physician wait time and length of visit, and an adverse impact on length of stay. These results provide weak support for Hypothesis 4, but may be reason for optimism for HIT-HIE investments in the future.

Overall, the benefits of HIT for care coordination were evident in adverse drug events and hospital readmissions, particularly for clinical care summary documentation and discharge instructions, care summary documentation, and clinical decision support, which are three significant care coordination measures of HIT-HIE. This study has shown modest evidence that CCD, CDISC, and CDSS may effect quality and outcome measures by improving care coordination. These results may be subject to the inclusion/exclusion criteria for this particular study. This study has also shown that HIT-HIE is evidenced to have more favorable process outcomes in emergency departments. Emergency departments require immediate and quick access to clinical information. This study did not find evidence of effects of HIT-HIE on hospital costs. This null finding will be discussed further in the next section. On the whole, the benefits of available patient data through HIT-HIE for clinical care are modest, yet promising. Health care providers armed with patient data can make more informed and timely decisions about patient care. As hospitals increasingly seek out ways to access their patient's information even at external providers, the measures of HIT-HIE will become increasingly meaningful and useful to that end. The next section will describe the limitations of this study.

F. Limitations

When interpreting results of this study, we must consider several limitations. First, HIT-HIE implementation is still fairly recent. Many hospitals may have implemented HIT within the past 3 years since the launch of meaningful use initiatives, as a result of monetary incentives for HIT-HIE implementation. As with the agricultural and transportation industries, there may simply not have been enough time elapsed to determine significant effects of HIT-HIE measures on healthcare outcomes and/or cost. The effects of HIT-HIE may not become evident for 10 to

15 years (Hillstead, Bigelow, Girosi, Meili, & Scoville, 2005) (Walker J. , et al., 2005). Lack of significance in most measures of HIT-HIE used in this study may be simply a result of the measures selected. Future work highlighting different measures of HIT-HIE may see different results. A further limitation is the fact that this study does not take into account lagged adoption times for the different technologies. As a result, I am unable to make a definitive statement about the difference between early adopters and late adopters in our outcome measures.

Furthermore, as a cross-sectional study, my analysis may be vulnerable to confounding non-observable factors in the AHA data. I evaluated process and quality outcomes for 5 conditions, among Medicare beneficiaries. HIT-HIE use could have different effects on outcome meaures for other medical conditions, and with other HIT-HIE measures. Another limitation of this study is the fact that the NHAMCS data contains responses for EMR for a relatively small number of hospitals. This may bias the data. However, as the survey continues, and is inclusive of more recent years, meaningful use initiatives will reflect in the survey results.

G. Policy Implications

On the whole, my results suggest that HIT-HIE made modest gains towards improving quality of healthcare delivery, and made no progress towards improving costs to date. These findings have direct policy implications for the use of HIT-HIE for care coordination, and meaningful use provisions. Three measures of HIT-HIE were associated with modest improvement in outcomes, while HIT-HIE use in Emergency Departments slightly more promising results for efficiency. As meaningful use enters it's second phase, these results are on par with somewhat dampened expectations for HIT-HIE use and success in academic literature.

The U.S. Department of Health and Human Services (HHS) authorized significant fnancial incentives for Medicaid and Medicare for health care providers who demonstrate meaningful use of technology to improve health care outcomes while reducing cost. HHS has also imposed stiff financial penalties for those providers that fail to demonstrate meaningful use. These incentives and penalities are centered on specific attributes of HIT-HIE adoption, such as the adoption of certified EHR systems, electronic prescribing, information exchange, and other measures. While this study shows modest gains from the use of HIT-HIE on specified outcomes, they underscore the Federal government's approach to define the expectations of the meaningful use of technology, with requirements becoming increasingly stringent over time. Demonstration of meaningful use will ultimately allow providers to access and transmit the information that is most critical to patient care and outcome improvement. Given that the Federal Government has invested so much on these technologies, my results suggest that the benefits of HIT/HIE-HIE in particular- may become evident once there is a critical mass of participant hospitals and health systems. This requires a sustained and concerted effort to create the infrastructure across the U.S. at the state level to exchange data among hospitals and providers. One barrier to HIT-HIE is the lack of business incentive for providers and vendors to share robust clinical information across settings of care. More specifically, hospitals have not yet been convinced of the added value of participation that would warrant an investment in HIE. Furthermore, most long-term post-acute care facilities (LTPAC) and behavioral health facilities are not eligible for incentive payments, thus making them less likely to participate in HIE. Limited HIE capacity also creates barriers to participation for skilled nursing facilities and rehabilitation hospitals (Wolf, Harvell, & Jha, 2015). Taken together, this can create gaps across care providers, paricularly for patients with complex cases, or those that seek care at different facilities. Initial Federal and state funding is necessary to create more incentives for these facilities to increase participations, switching to private sources for sustainability once federal and state funding has ended. Currently, CMS provides funding for the design and development of HIE infrastructure. However, this funding is provided specifically for the Medicaid EHR incentive program, and does not support funding for maintenance costs.

As funding ends for HIEs at the state level, policies should include variable and sustainable funding sources. Current pricing policies do not generate enough revenue to cover costs, which could render HIEs unsustainable in the long run. Furthermore, policymakers must consider carefully costs associated with startup and implementation, general and administrative costs, consulting fees, IT hosting services and data service costs. Next, HIEs must consider what value they provide to the stakeholders. The functions and services available to stakeholders must be such that mutually beneficial relationships develop, and are maintained by virtue of the services offered (Truven Health Analytics, 2011). Finally, there is a difference between implementation for cost reduction purposes, and increasing efficiency. However, HIEs will need to generate revenue in order to be sustainable. It may seem sundry for health care organizations to want to generate profit off of tools that could reduce health care costs. However, revenue generation can help incentivize a wider network of HIE participants. As such, policymakers should ask and consider questions in the area of revenue and profit generation.

Revenue generation is a serious consideration for HIEs. How will the HIE charge stakeholders for their services? What package of services will be offered? How will fees be determined? These are all the critical questions that policymakers will need to consider to address and achieve HIE sustainability.

Policymakeres may look to Minnesota as an example of successful HIE implementation. Minnesota employs a not-for-profit public-private statewide, secure electronic network to share clinical and administrative data among providers in Minnesota and bordering states. To date, 4.2 million out of 5 million residents in Minnesota participate, with the option to opt out of participation. With an annual subscription fee based on total patient volume, Minnesota circumvents reliance exclusively on public and government funding. Involvement of insurers and other private consintuents may also facilitate stakeholder ownership, thus increasing participation. Successes in Minnesota have further incentivized the adoption and implementation of HIT measures in order to maximize positive health and cost outcomes.

My findings have significant implications for how the estimated $20 billion in HIT incentives are allocated for both regional extension centers and HIEs. CDISC, CCD and CDSS were the only measures of HIT-HIE that demonstrated a modest level of significance in this study, and all three measures are integral to the exchange of clinical information, and transition of care between hospitals and providers. Health Information Exchanges as an entity are contingent upon the participation of increasingly large networks of providers in order to reap the benefits of information exchange. However, with administration changes during the election cycle, many states are left to flounder, searching for sustainable ways to fund and finance HIEs. Use of states like Minnesota as case studies in HIE funding could increase HIT-HIE adoption and HIE networks.

Earlier in this paper I discuss two models for technological adoption: ITPOSMO and ISTA. Health care institutions may reference and incorporate either or both of these models in provider training, if we are to realize maximium productivity gains from HIT-HIE. Current hospital organizational structures and processes may hinder productivity gains. Cutler (2010) contends that this may be the case, suggesting that organizational change could improve hospital efficiency. Hospital administrators and policymakers may consider incorporating these models into overall implementation plans. The need to manage expectations for HIT-HIE implementation and outcomes associated with it are especially important given the results of this study. Incorporation of the ISTA model in provider and user training for HIT-HIE facilitates consideration of the socio-technical and cultural considerations surrounding process/work flows, and ways to maximize HIT-HIE in unique settings. The ITPOSMO model also fosters end user development, and can help resolve conception-reality gaps in HIT-HIE implementation. Taken together these two strategies can help mitigate unintended consequences of HIT-HIE implementation, improve process/work flows, and ultimately increase efficiency leading to more favorable outcomes.

Over time, as providers become accustomed to use of the technology in patient care, coupled with increasingly robust meaningful use requirements, we could see the actualization of improved outcomes where effective utilization meets technology adoption. Furthermore, users may require time to adapt to HIT-HIE measures before process and efficiency gains are realized. The productivity paradox referenced earlier in this paper is a widely accepted explanation for why the results suggest such modest gains from HIT-HIE implementation. While difficult to test empirically, this possibility cannot be ruled out by this study. The argument for continued investments and implementation of HIT-HIE is premised on the fact that while we see modest gains now, we may see more robust gains in the future.

VI. CONCLUSION

This study has analyzed the effect of Health Information Technology (HIT) adoption on quality outcomes. Drawing on the literature surrounding HIT-HIE and health care outcomes, I conduct my empirical analysis by looking at key hospital quality inidicators for a selected patient population with both severe and chronic diseases. I also use the robust NHAMCS survey data to test effects of HIT-HIE on emergency department outcomes.

Certain measures of HIT-HIE resulted in weakly positive effects on adverse drug events and hospital readmissions. In the emergency department, HIT-HIE resulted in positive quality outcomes for length of stay, length of visit and physician waiting time. On the other hand, measures of HIT-HIE showed no effect on cost or overall length of stay. The evidence suggests that HIT-HIE, while not yet compelling, still has potential to improve health care outcomes. This study may serve as justification for continued, albeit conservative funding for HIT-HIE implementation. Further research by academia and policy makers may see even greater returns to HIT-HIE implementation in the future.

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