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LOCAL HEALTH DEPARTMENT ADOPTION OF HEALTH INFORMATION TECHNOLOGY AND ITS IMPACT ON POPULATION HEALTH

by

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A dissertation submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy
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ABSTRACT

Since the enactment of the HITECH Act in 2009, the US has invested billions in building a robust health information technology (HIT) infrastructure that is secure, capable of the electronic transfer of data and allows for real-time access of patient medical data, among others. This empirical study explored the driving forces (coercive, mimetic, and normative) in the adoption of HIT (i.e. EHRs and HIEs) by local health departments (LHDs) and how it has impacted the population health of counties in the US. The researcher conducted a cross-sectional, quantitative study using secondary data sources. The study included data on 505 local health departments and 433 counties' population health data. Institutional theory guided this research and generalized estimating equations, logistic regression, and multiple linear regression were utilized to analyze health IT adoption by LHDs and its impact on county-level health outcomes.

Results showed that normative forces, measured by the employment of IS specialists was most impactful in the adoption of both EHRs and HIEs. Mimetic forces, measured by the completion of a CHA and coercive forces measured by the implementation of the HITECH Act were not found to be statistically significant in the adoption of EHRs or HIEs. Finally, EHR adoption was statistically significant at improving population health at the county level.

This research study has contributed in three areas: 1) to fill a knowledge gap on the impact of health IT adoption by LHDs on health outcomes; 2) to formulate a theoretically grounded framework to study population health and its variability; and 3) to identify target areas for public health interventions. In conclusion, a substantial amount of resources dedicated in creating a robust health IT infrastructure requires close analysis of the impact health IT has on the population health of our nation.

This is dedicated to my parents Siu Han and Siu Ngan Yeung for your unconditional love and encouragement. You have instilled in me the value of hard work and the importance of a strong education and have always provided the support I needed to pursue my dreams.

To my husband, this would not have been possible without your love and support. You inspire me each and every day.

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CHAPTER ONE – INTRODUCTION

Background

The United States has had limited success in improving personal health and well-being of American citizens, although concerted efforts have been made to improve the health of the population (McGinnis, 2006). Despite the many health gains that have been observed in the past decades, the United States continually ranks at the bottom for many measures of health compared to other developed nations that are a part of the Organization for Economic Co-operation and Development (OECD). For example, in 2013 the life expectancy at birth was 78.8 years in the United States, compared to an average of 80.5 years amongst all other OECD countries, based on this life expectancy the United States was ranked 27th out of 34 participants (Fineberg, 2012; OECD, 2015). More recently, the life expectancy at birth in the United States in 2015 remained at 78.8 years (Xu, Murphy, Kockanek & Arias, 2016). Furthermore, obesity rates among adults in the United States are the highest amongst OECD countries at an estimated 35% of the population. The United States also lags behind in the prevention of hospital admissions amongst those who have a chronic illness such as asthma, chronic obstructive pulmonary disease (COPD), and diabetes (OECD, 2015). While the United States falls behind in many health measures compared to other OECD countries, the United States does fare better in other areas, such as the decline in the percentage of adults who smoke cigarettes daily from 33.5% in 1980 to 14% in 2013. Further, the United States also performs well in providing acute care in hospitals for the treatment of heart attacks and stroke and for the treatment of breast and colorectal cancer (OECD, 2015).

Much of the population health successes can be attributed to our public health system and the preventative programs and initiatives that are implemented by local health departments (LHDs) to prevent disease and the promotion of disease prevention and control. However, more can be done. As a nation, we continually spend much more per capita on healthcare services. Yet, compared to other developed nations that spend half as much as the United States per capita, the United States fares no better on many health outcomes (Fineberg, 2012; Institute of Medicine, 2012; OECD, 2015).

Our nation understood the need for a strong health information technology infrastructure to improve the health of our nation and in 2009, the United States passed the Health Information Technology for Economic and Clinical Health (HITECH) Act as part of the American Recovery and Reinvestment Act of 2009 (U.S. Department of Health & Human Services, 2011). The purpose of the HITECH Act was to drive the country "toward a nationwide, interoperable, private, and secure electronic health information system" (Blumenthal, 2010, p. 382). David Blumenthal, the former National Coordinator for Health Information Technology from 2009 to 2011 (The Commonwealth Fund, 2015), described information as the "lifeblood of modern medicine" (Blumenthal, 2010). Thus, health information technology (IT) is considered to be the mechanism for delivering information necessary to improve population health (Centers for Disease Control and Prevention, 2016).

Population health is largely driven by the functions of local health departments (LHDs) as they lay the groundwork for our nation's public health infrastructure. Their multiple functions include controlling disease outbreaks, providing women and children services, responding to natural disasters, implementing programs and policies to reduce chronic disease stemming from social determinants of health, and providing healthcare services (Willard, Shah, Leep, & Ku,

2012). This list is not exhaustive, but it shows the depth and reach of LHDs and their goals of keeping the local community protected against harm. Further, with the passing of the HITECH Act, health information technology is seen as an important foundation for improving healthcare quality and efficiency.

Health information technology describes the many types of technology or tools used in the healthcare field. Examples of health information technology used by LHDs include electronic health records (EHRs), health information exchanges (HIEs), immunization registries, electronic disease reporting systems, and many other types of technology. When health information technology is used in public health to address population health goals, it is known as public health informatics (Fond, Volmert & Kendall-Taylor, 2015). Wan (2006) defined informatics as "an interdisciplinary science employing information on science, information technology, and statistics." Public health informatics represents the process of using data and information gathered from health information technology to make informed, evidence-based decisions that can transcend interdisciplinary fields within the public health sector (Fond et al., 2015). Yasnoff, O'Carroll, Koo, Linkins, and Kilbourne (2000) defined public health informatics as "the systematic application of information and computer science and technology to public health practice, research, and learning." Thus, public health informatics uses health information technology to collect data. Once the data are collected, they are analyzed to become useable information and knowledge so that appropriate stakeholders can make important decision. With the passing of the HITECH Act and the millions of dollars invested into our nation's health information technology infrastructure, now more than ever it is imperative to assess how LHDs are leveraging health IT to improve population health.

Significance of the Study

In 2009, the Institute of Medicine's (IOM) Committee on Public Health Strategies to Improve Health published the first of a three-part series on our nation's public health. Titled *For the Public's Health: Revitalizing Law and Policy to Meet New Challenges*, the first publication put forth several recommendations, of which two demonstrate the significance of health information technology in the public sector (Institute of Medicine, 2009):

> **Recommendation 1:** Provide leadership to a renewed population health information system through enhanced coordination, new capacities, and better integration of the determinants of health.
>
> **Recommendation 2:** Support and implement the following to integrate, align, and standardize health data and health-outcome measurement at all geographic levels:
>
> a. A core, standardized set of indicators that can be used to assess the health of communities.
>
> b. A core, standardized set of health-outcome indicators for national, state, and local use.
>
> c. A summary measure of population health that can be used to estimate and track health-adjusted life expectancy for the United States.

These recommendations bring to light the importance of strengthening our public health infrastructure but also the need to leverage health information technology to create a standardized and unified public health information technology infrastructure. This study can bring to light the impact of health IT, specifically EHRs and HIEs on population health. Consequently, policies can be created to influence the adoption of IT by LHDs.

The passing of the HITECH Act in 2009 spurred the adoption of health information technology across the nation as a driver to improve clinical care (Shah, Leider, Castrucci, Williams, & Luo, 2016). The adoption of electronic health records (EHRs) is widely believed to result in healthcare cost savings, improved healthcare quality, reduced medical errors, engagement of patients and improvement of the overall healthcare system (Blumenthal, 2010; Buntin, Burke, Hoaglin, & Blumenthal, 2011; Hillestad et al., 2005). Although the HITECH Act is intended to affect clinical care practice and cost containment, it does have profound implications for LHDs. LHDs across the nation are already employing health information technology (HIT) in some capacity, including the participation in state health information exchanges (HIEs), EHRs, immunization registries, electronic syndromic surveillance (ESS), and electronic laboratory reporting. EHRs, HIEs, ESS and electronic laboratory systems allow LHDs to access and process data in real-time. If the IT systems at the LHDs can transfer patient data to local hospitals and vice versa, the ability to track those who misuse the emergency department or are labeled as "frequent-flyers" can be tracked, which reduces duplicative testing and can address access to care concerns for the low-income population. Moreover, the detection of disease outbreaks, bioterrorism events and foodborne illnesses is possible because of HITs such as ESS (Shah, Leider, Castrucci, Williams, & Luo, 2016). Lastly, to improve HIT interoperability across states and local areas, funding from the HITECH Act supported state HIEs to promote the electronic exchange of data (Gold & McLaughlin, 2016).

The adoption of HIT in hospitals has been well documented and studied; however, little is known about the role of HIT in shaping the operations of LHDs, particularly in the use of electronic health records and health information exchanges. Moreover, the implementation of public health HIT is rarely documented or reported, in particular its impact on healthcare

outcomes within a population. The literature under-investigates the role of HIT in the public health sector and its impact on population health (Adler-Milstein et al., 2014; McCullough, Zimmerman, Bell, & Rodriguez, 2015; Shah, Leider et al., 2016).

The government recognizes the importance of a strong health information technology infrastructure. The advancement of health information technology has the potential to improve the effectiveness and efficiency of LHDs in the execution of their functions in disease prevention, disease surveillance, data collection, and many other functions. More importantly, with a changing healthcare landscape and new threats to the safety of communities, it is important to analyze the effectiveness of the public health IT infrastructure (Wan, 2010; Yasnoff et al., 2000).

The dearth of outcome-related literature undervalues the contributions of the public health system to the overall population health. This study aims to provide a conceptual framework from an institutional theory perspective to understand the driving forces of health IT adoption by LHDs. Significant policy implications can be derived from this study as we seek to understand the impetus to the adoption of health IT by LHDs. Lastly, this research aims to analyze the impact of the adoption of health information technology by LHDs on county-level health outcomes.

Research Design

This cross-sectional, quantitative study uses secondary data from the National Association of County & City Health Officials (NACCHO), National Profile of Local Health Departments study (Profile Study) from years 2008 and 2013, and the 2016 County Health

Rankings data produced by the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute (National Association of County and City Health Officials, 2008, 2013). Using generalized estimating equations, logistic regression, and multiple linear regression, this study analyzes the impact of health IT adoption by LHDs on county-level health outcomes as guided by institutional theory.

CHAPTER TWO – CONCEPTUAL FRAMEWORK

This research study is guided by institutional theory. Institutional theory has been used by various researchers to explain how organizations respond to internal and external forces, leading to changes at the organization level (Jensen, Kjaergaard, & Svejvig, 2009). Institutional theory postulates that organizations mirror rational organizations based on socially constructed reality within their external environment (Meyer & Rowan, 1977). Known as isomorphism, organizations become increasingly homogeneous over time. Coercive, mimetic and normative are three types of isomorphic forces that can explain organizational behaviors and practices (DiMaggio & Powell, 1983). Coercive forces stem from the external environment, while both mimetic and normative forces tend to stem from within an organization (Frumkin & Galaskiewicz, 2004).

The DiMaggio and Powell (1983) discussion of institutional theory follows similarly to the work of Meyer and Rowan (1977). DiMaggio and Powell argued that early adopters of innovation and engagement in isomorphic behavior are compelled by a desire to improve their organizational performance. Conversely, later adopters are simply adopting just to receive legitimacy rather than for the betterment of the organization (DiMaggio & Powell, 1983). Thus, organizations become isomorphic with their environment even if the decision to do so may not be the most strategic or suitable for that organization (George & Chattopadhyay, 2006; Kaissi & Begun, 2008; Suchman, 1995). Consequently, the driving forces of isomorphic behavior amongst LHDs in the adoption of health IT can be analyzed and understood by the three mechanisms of institutional change: coercion, mimetic behaviors, and normative forces. A discussion of the three forces are further explained in the following sections.

Coercive Isomorphic Mechanism

Coercive isomorphism can be through informal and formal pressures exerted by the external environment. Informal pressure can be in the form of persuasion from other organizations, whereas formal pressure may come from mandated laws as required by the government. Coercion stemming from the power of governmental bodies to enact laws and regulations can drive institutional change (Kaissi & Begun, 2008). This can be seen with the passing of the HITECH Act and the potential penalties imposed for failure to adopt and demonstrate meaningful use of a certificated EHR.

There are five main goals of HITECH:

- Empower the Office of the National Coordinator for Health Information Technology (ONC) to develop a strategic approach in standardizing health IT across both the public and private healthcare sectors
- Establish unified standards and certification to allow for health information exchange, data collection, and clinical use in a meaningful way
- Build the infrastructure for health information technology
- Protect the privacy and security of health information to ensure sensitive patient information is accessed only by those who have authorization to do so, which includes the strengthening of the Health Insurance Portability and Accountability Act (HIPAA)
- Deliver incentive payments through Medicare and Medicaid to providers for adopting Electronic Health Records (EHR) and using them meaningfully (Stark, 2010).

HITECH provided $30 billion to promote the adoption and effective use of healthcare IT in ensuring a robust healthcare delivery system (Adler-Milstein et al., 2014). Undoubtedly,

health IT adoption among hospitals and professional practices has increased, especially since 2010, spurred by the implementation of HITECH. Since 2010, EHR adoption has increased fourfold, and between 10 and 15% of hospitals are adopting and using EHRs every year. In 2014, 97% of reporting hospitals were using a certified EHR, while 83% of office-based physician practices used an EHR system (Adler-Milstein et al., 2014). Further, “as of September 2015, more than 307,000 Medicare-eligible professionals (physicians, dentists, podiatrists, optometrists, and chiropractors) and nearly 4,500 Medicare-eligible hospitals met at least Meaningful Use (MU) Stage 1 requirements” (Gold & McLaughlin, 2016).

While the HITECH Act directly impacts hospitals and clinicians in both the private and public sectors, there are implications that can potentially impact how LHDs receive, use, and track public health information as the adoption rate increases amongst hospitals and clinicians to enhance population health (Gold & McLaughlin, 2016; Shah, Leider et al., 2016; Stark, 2010). Provisions in the HITECH Act were implemented in stages, and while reporting of immunization information, electronic laboratory results, and syndromic surveillance were optional in Stage 1of MU, by Stage 2 of MU, reporting of immunization information and electronic laboratory results became mandatory for eligible professionals (Gold & McLaughlin, 2016). Reportedly, by February 2014 “among eligible hospitals, 54% submitted immunization data to public health agencies, 20% syndromic surveillance data, and 15% laboratory results” (Gold & McLaughlin, 2016).

More importantly, the purpose of the HITECH act was two-fold: to promote the adoption of health IT and to use it in a meaningful way. To-date, the focus has shifted to the fundamental use of health IT rather than adoption since most hospitals and professional practices have some form of EHR (Gold & McLaughlin, 2016). Still, barriers in using health IT meaningfully exist,

and the objective of the legislation has fallen short of its intentions. The reality is that interoperability between EHR systems still remains an issue and limits the ability to exchange medical information across platforms (Gold & McLaughlin, 2016). Consequently, health IT has the ability to connect LHDs with hospitals and physician practices but only if the health IT adopted by LHDs are interoperable with their local communities' health IT systems. The passing of the HITECH Act is used to measure coercion as the mechanism of institutional change in the adoption of health IT (Zhang & Wan, 2007).

Mimetic Isomorphic Mechanism

Kaissi and Begun (2008) described mimetic behaviors as a form of imitation. During times of heightened uncertainty, organizations tend to mimic exemplar organizations or their competitors. Environmental pressure forces organizations to mimic their counterparts even when organizations are not comfortable with change, which often may not even be the most appropriate for that organization (D'Aunno, Vaughn, McElroy, 1999; Kaissi & Begun, 2008). As March (1981) found that if enough "actors do things in a certain way," others will follow suit because this new behavior has now been institutionalized (Haveman, 1993).

To measure mimetic isomorphism, this study examines a LHD's completion of a community health assessments (CHAs) and planning initiatives.

> "CHA can be defined as regularly and systematically collecting, analyzing, and making available information on the health of a community, including statistics on health status, community health needs, epidemiologic and other studies of health problems, and an

analysis of community strengths and resources" (National Association of County & City Health Officials, 2014).

CHA uses both quantitative and qualitative methods to collect data on the community of interest. The topics of interest can include mortality, morbidity, social determinants of health and health inequity, as well as services and activities provided by the public health system. LHDs are not required to conduct a CHA, however, a provision within the Affordable Care Act (ACA) requires nonprofit hospitals to conduct a community health needs assessment. Additionally, nonprofit hospitals are required to engage public health experts in their assessment of the needs of their local community (Rosenbaum, 2013).

Performing a CHA allows LHDs and other public health programs to prioritize activities and programs to meet the most pressing health needs of their community, which is why a CHA provides information for informed decision-making (National Association of County & City Health Officials, 2017a, 2017b).

For CHAs to be an effective mechanism of driving organizational change, collaboration and information-sharing is an important component. Through collective action, LHDs have the opportunity to mimic other similar LHDs especially if LHDs are faced with uncertainty in deciding whether or not to adopt HIT or to strengthen their HIT infrastructure. If the implementation of HITs is leading to improved population health (i.e. decrease in premature death and improved health-related quality of life), it is hypothesized that conducting a CHA is a predictor of EHR and HIE adoption by LHDs.

Normative Isomorphic Mechanism

Normative isomorphism describes professionalization within an organization. DiMaggio and Powell (1983) further expands on normative isomorphism as two processes. First, members of the same profession (i.e. nurses, doctors, university professors, lawyers, IS specialists) receive similar training in their respective occupation. Because of this, professionals are socialized and trained to similar worldviews. Second, each occupation has their own professional and trade organizations in which professionals can diffuse ideas and share knowledge amongst individuals of the same profession (Mizruchi & Fein, 1999). As a result, professionals of the same profession are very similar to their counterparts in other organizations. Moreover, in times of uncertainty, transfer of knowledge between professionals of the same profession can occur which can bring about legitimacy (DiMaggio & Powell, 1983).

Further understanding of normative isomorphism is explained by Larson and Collins (as cited in DiMaggio & Powell, 1983) which they describe normative pressure "as the collective struggle of members of an occupation to define the conditions and methods of their work, to control "the production of producers," and to establish a cognitive base and legitimation for their occupational autonomy."

To operationally define normative isomorphism, this study uses the employment of information system specialists (yes/no) to measure normative isomorphism. Specifically, whether employing information system specialists will drive the implementation of health IT (i.e. EHRs and HIEs) amongst LHDs.

Health IT systems such as immunization systems and programs that are federally or state sponsored such as Women, Infants and Children (WIC) programs have their own information

system and are largely universally adopted by all LHDs. Additionally, disease reporting and outbreak management systems have also been adopted by the majority of LHDs (NACCHO, 2007). However, the percentage of LHDs adopting EHRs and HIEs are much fewer at 22% and 13% respectively according to the 2013 Profile Study (NACCHO, 2007, 2014). Because LHDs have had these legacy systems in place, IS specialists would already be on staff or the LHDs could have cross-trained their employees on how to use these systems.

Because of the push to adopt EHRs and HIEs, there is now a greater need to employ IS specialists rather than cross-train existing LHD staff members on how to use these health IT systems. Thus, LHDs need to employ IS staff members who can apply their skills and knowledge on HIT to the practice of public health. As a result, the employment of health information system (IS) specialists can drive organizational assimilation. Their expertise (Jensen et al., 2009) in the IT field can guide top managers at LHDs on the benefits and drawbacks of implementing health IT. Further, IS specialists are professionally trained and are responsible for health IT duties daily. Thus, they can offer informed knowledge on health IT implementation and act as the impetus to drive the adoption of EHR and HIEs. Lastly, as information specialist professionals share their knowledge through their professional associations, they are able to garner new knowledge from their colleagues on HIT. This is especially important for those LHDs that have not implemented EHRs or HIEs but have investigated or are planning to implement HIE which can help to spur the adoption of EHRs and HIEs more quickly.

In summary, guided by institutional theory, this study will operationally define coercive mechanism with the passing of the HITECH Act, mimetic isomorphism will be defined by the completion of a CHA and the employment of information system specialists as a measure of normative isomorphism.

Figure 1 illustrates the present study's conceptual framework used to analyze the relationship between LHD's health IT adoption and the impact on health outcomes at the county level. The independent variable, health IT adoption, is measured by a variety of indicators including electronic health records and health information exchanges. The dependent variable, health outcomes, is measured by an overall health outcomes variable, which is composed of premature death (YPLL) and health-related quality of life. Guided by institutional theory, the study examines the effects of all three institutional mechanisms—coercive, mimetic, and normative—on the adoption of health information technology by LHDs. Coercive isomorphism is measured by the passing of the HITECH Act of 2009.   Mimetic isomorphism is measured by LHD's completion of a community health assessment. Normative isomorphism is measured by LHDs employment of information system specialists.   Demographic and socio-economic variables of the population, including education level, race, and median household income, are included as controls. Control variables are also included for LHD—population size served, revenue, and LHD governance classification (state, local or both)—to account for other factors that may influence health outcomes.

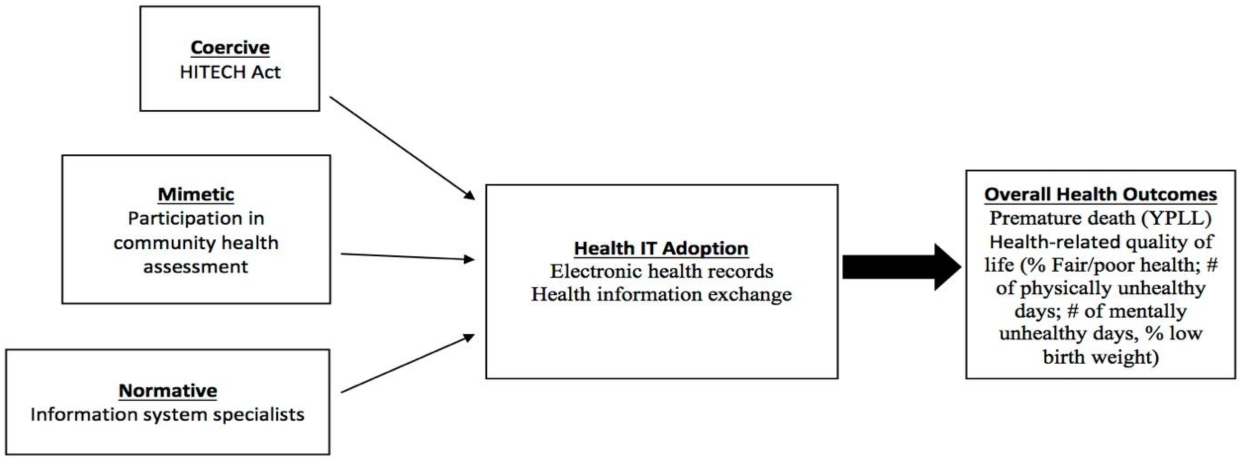

Figure 1: Conceptual Framework

Based on Figure 1, seven testable research hypotheses were formulated, using institutional theory coupled with organizational performance and outcomes assessment. The three isomorphic mechanisms, reflecting organizational context and structural domains, directly influence organizational performance. Organizational performance directly influences health outcomes at the population (county) level. In addition, other contextual or ecological variables such as governance structure, population size, socioeconomic status (race, education and income level), and LHD revenue are considered as control variables, without including them as major hypotheses for this investigation.

CHAPTER THREE – LITERATURE REVIEW

This chapter presents a literature review germane to institutional theory and health IT adoption, county LHDs, the adoption of health IT by LHDs and the impact of LHD adoption of health IT on population health. The first section provides a review of the current body of literature on institutional theory and health IT adoption. Next, population health and public health are defined to understand the distinction between the two concepts. The section then provides a review of the current literature on population health. After the presentation of the foundational knowledge of population health, the literature on health outcomes—specifically premature death (mortality) and health-related quality of life—is explored, in particular why these two measurements combined to form the overall health outcomes score are appropriate to provide a snapshot of the health of a county. The final section of this chapter provides an overview of county-level LHDs, including their roles and responsibilities, differences in LHDs by county, the adoption of health IT by LHDs and the adoption of health IT and its impact on health outcomes.

Institutional Theory and Health IT Adoption

The body of literature on information systems (IS) and IT adoption as explained through institutional theory is abundant, yet the adoption of health IT by LHD as explained by institutional theory is less prominent. In addressing the former, because IS implementation at the enterprise level is becoming ubiquitous across different industry sectors, many studies have been conducted through the lens of the institutionalist perspective. For instance, a study by Teo, Wei

and Benbasat (2003) examined the driving forces in the adoption of financial electronic data interchange (FEDI) at Singapore-based organizations. Their study found that all three forces—coercive, mimetic and normative—were significant in influencing the intention to adopt FEDI. Coercion was measured by the perceived dominance of its suppliers and customers who have adopted FEDI and by the adoption of FEDI by the parent corporation. Mimetic was measured by the extent of adoption of FEDI among its competitors and the perceived success of their competitors who have adopted FEDI. Normative was measured by the extent of adoption of FEDI among its suppliers and customers and the participation in associations.

In another study, Liang, Saraf, Hu, and Xue (2007), guided by institutional theory, studied how internal forces from top management mediated the influence of external institutional pressures on Enterprise Resource Planning (ERP) system assimilation in mid- to large-size organizations. Top management members translate external influences into actionable changes to organizational structures and the establishment of new organizational policies. The authors states that top managers can also be influenced by external forces and it is these influences that drive organizational changes. Mimetic force was measured by the perceived extent to which competitors have benefitted from the implementation of ERP. Coercive force was measured by the perceived competitive condition and the incentives and requirements from the local government and industry associations. Lastly, normative force was measured by the perceived extent to which similar organizations within their network have adopted an ERP system and the extent to which the government and industry agencies promote the adoption of ERP systems. Results from the study demonstrated that mimetic, and coercive were found to be statistically significant, while normative was not found to be statistically significant (Liang, Saraf, Hu, and

Xue, 2007). The aforementioned studies show how institutional theory has been applied in other businesses and industries.

A few empirical studies have looked at the institutional mechanisms driving the adoption of innovation in healthcare organizations. One study conducted by Sherer, Meyerhoefer and Peng (2016) was interested in using institutional theory to examine the adoption of EHRs in ambulatory medical practices. Coercive forces were measured by the percentage of revenue received from Medicare and Medicaid. Mimetic forces were measured by the percentage of physicians practicing in the same specialty who have either fully or partially implemented an EHR system. Lastly, normative forces were measured by the percentage of physicians in the same hospital referral region who have fully or partially implemented an EHR system. Results showed that mimetic was partially supported. It was found to be significant in 2008 (before HITECH), but not in 2012 (after HITECH). Normative was statistically significant and coercive was also partially supported.

Another study found that licensing and accreditation was strongly correlated with the adoption of human immunodeficiency virus (HIV) prevention practices amongst the nation's outpatient substance abuse treatment units (D'Aunno et al., 1999). In another study explaining variations in nursing home quality, coercive isomorphism was found to be most impactful on nursing home quality, while normative isomorphism (i.e., the number of RNs/resident/day, the number of LPNs/resident/day, professional training) was less impactful in improving nursing home quality (Zhang & Wan, 2007). Finally, Currie and Guah (2007) conducted a study on the adoption of a large-scale IT implementation project known as the National Programme for Information Technology (NPfIT) in the UK, the world's largest civil IT program. Their study was theoretically based on a Scott, Ruef, Mendel, and Caronna (2000) US-based study that

examined changes in healthcare organizations guided by multiple theories, one of which is institutional theory.

Evolution of the Term Population Health

This section delves into the literature surrounding the evolution of defining and conceptualizing population health. Further, this section provides a discussion of the differences between population health and public health. Although the term population health is not new, in the last decade or so it has evolved from having multiple definitions and interpretations to being more precisely defined and agreed upon by scholars (Kindig, 2007, 2015; Kindig & Stoddart, 2003). First popularized in Canada, the term population health is gaining more prominence here in the U.S. Kindig (1997) defined population health as "the aggregate health outcome of health adjusted life expectancy (quantity and quality) of a group of individuals, in an economic framework that balances the relative marginal returns from the multiple determinations of health." Others believe population health incorporates social, economic, biological, and environmental determinants to help shape the health of a population (Kreuter & Lezin, 2001), while still others define population health as simply goals to achieve to improve the health of a population (Kindig & Stoddart, 2003).

For purposes of this study, population health will be defined as the health of a population at the county level as measured by health outcomes (premature death and health-related quality of life) through the impact of determinants such as health IT (Kindig & Stoddart, 2003). In contrast to medical care, where the focus is on the individual, population health focuses on the collective health of a population (Kindig, 2007; Shi & Singh, 2012). Further, as mentioned

previously, population health is impacted not only by the collective health of the population but also by other determinants, including geographic, demographic, environmental, social, and many other external influences on health outcomes (Kindig, 2007).

Difference Between Population Health and Public Health

The terms population health and public health have often been used interchangeably. However, these terms are not synonymous. Public health is a subsystem of the U.S. healthcare system, while medical care makes up the other half (Ozcan & Khushalani, 2016, Woolf & Aron, 2013). Together, these two subsystems provide healthcare and a safety net for the entire U.S. population through public health agencies including LHDs. Public health is concerned with the population rather than the individual. It identifies environmental, social, and behavioral determinants that may be pathogenic sources or causes of disease or poor health. Thus, the public health system develops population-wide interventions to minimize and reduce the risk factors that can cause harm to people (Shi & Singh, 2012). Resource utilization offers another distinction between population health and public health. Public health relies on federal or state funding and/or resources, whereas population health relies on private or local resources. Last, public health seeks to promote efforts to prevent and control the presence of diseases through campaign awareness, used of syndromic surveillance systems to detect disease outbreaks and bioterrorism, offer public education and implement community outreach projects.

Although public health does focus on the population rather than the individual, it is a system that seeks to provide care and protection to the community. In contrast, population health describes the health of a population as measured by various healthcare outcomes.

Consequently, it is important not to use the terms population health and public health interchangeably, as they have differing meanings. Table 1 summarizes the distinction between population health and public health.

Table 1: Summary of Population Health and Public Health

	Population Health	**Public Health**
Definition	Describes the health of the population and its determinants	Subsystem of the US healthcare system that ensures that the environmental conditions allow people to live a healthy life.
Purpose	Measures the health of the population by employing various health outcomes including life expectancy, premature death, health-related quality of life and many other measures.	Develops population-wide interventions to minimize and reduce the risk factors of disease outbreaks, employ surveillance, create awareness through community outreach and public campaign programs
Resource Utilization	Relies on private or local resources	Relies on federal or state funding

Current Studies on Population Health

State-Level Analysis on Population Health

To date, much of the literature on population health focuses on U.S. state-level analysis of population health. Since 1990, the United Health Foundation has been publishing the America's Health Rankings Annual Report (The Annual Report) providing a "state-by-state analysis of factors affecting the health of individuals and communities across America" (United Health Foundation, 2015). Their model consists of four categories: behavior, community and environment, policy, and clinical care. Multiple core measures make up each of the four

categories, and these elements interact to determine the population health of each state (United Health Foundation, 2015). This report provides a state-by-state benchmark to understand how the health of a state changes from year-to-year.

In 2014, the publication of the Commonwealth Fund's Scorecard on State Health System Performance analyzed all 50 states between 2007 to 2012 on over 34 indicators of healthcare access and affordability dimensions, prevention and treatment dimensions, avoidable hospital use and cost dimensions, and healthy lives dimensions (Radley, McCarthy, Lippa, Hayes, & Schoen, 2014). What the scorecard found was that overall, no meaningful improvement or decline in the state's performance was detected on two-thirds of the 34 Scorecard indicators. The indicators where states saw the most improvements included "immunizations for children, safe prescribing of medications for the elderly, patient-centered care in the hospital, avoidable hospital admissions and readmissions, and cancer-related deaths" (Radley et al., 2014). Moreover, a decrease in cancer-related deaths and lower premature mortality rates suggest better health outcomes as a result of improvements in medical care. Last, there were significant reductions of premature death (mortality amenable to healthcare and years of potential life lost) in 15 states (Radley et al., 2014).

This body of research suggests that population health is of importance and provides a detailed perspective on each state's commitment (or lack thereof) to its population through public health initiatives and the effects it has had on its population's health. This further suggests that there is a need for a more granular analysis beyond the state level. The weakness of a state-level analysis is the inability to provide a one-size-fits-all actionable policy to address population health needs. The geographical and demographic differences within each state make it difficult to address population health concerns at such a macro level. Although a state analysis

is critical in determining the health of each state, a more granular level such as at the county level is needed to provide a better analysis of each state's health of the population. A county-level analysis, which is what this study explores, will provide an in-depth look at county-level health outcome comparisons, which so far represents the gap in literature on population health studies.

Small Area Analysis on Health Outcomes

Ecologic studies "are empirical investigations involving the group as the unit of analysis" (Morgenstern, 1982), for example, small-area analysis studies. A review of relevant literature reveals literature identifying neighborhoods ("an area") influencing health outcomes (Bernard et al., 2007; Cummins, Curtis, Diez-Roux & Macintyre, 2007; Diez & Mair, 2010). Neighborhoods can be described as "places" where the daily lives of individuals (where they work, live, and play) contribute to health inequalities in everyday life. This conceptualization looks at the neighborhood as the provider of resources that influence population health (Bernard et al., 2007). Other available research on small-area analysis studies sought to determine the linkage between local area characteristics and health outcomes. In 2001, Pickett and Pearl (2001) conducted a meta-analysis on 25 studies (all before June 1, 1998) that focused on the effects of local-area social characteristics (or neighborhood socioeconomic context) on individual health outcomes, both domestically and abroad. Of the 25 studies, ten examined how neighborhood social factors caused mortality. Fourteen analyzed the impact of neighborhood social factors on morbidity, specifically infant and child health, chronic disease among adults, and studies of mental health. The remaining studies examined the impact of neighborhood social factors on health behaviors

(Pickett & Pearl, 2001). The interest in small-area analysis underpins the significance of environmental factors on the causes of ill health that scholars know cannot be based purely on individuals alone (Diez & Mair, 2010).

Finally, numerous studies on population health have identified income inequality as a determinant of population health (positive or negative), and this relationship continues to provoke dialogue and research amongst scholars. In 2006, Wilkinson and Pickett identified 168 analyses in 155 papers that reported research findings "on the association between income distribution and population health." Their research indicated that some studies found statistically significant associations between greater income inequality and poorer population health (87 studies). Thirty-seven studies found no statistically significant association between greater income inequality and poorer population health, and 44 studies showed mixed results where some but not all showed an association between greater income inequality and poorer population health (Wilkinson & Pickett, 2006). More important, of the 168 studies, 83 were populations from nation states; 73 studied population health at the state, region, or city level; and 45 were population health studies at the county, tracts, or parish level.

A 2003 study looking at the linkage at the county level between income inequality and depression (psychological dimension of health) among older Americans found a significant association between county-level income inequality and depression among older Americans. This study also substantiated the environmental effects on depression among older adults, including socioeconomic conditions and availability of transportation (Muramatsu, 2003). In a 2006 study conducted by Lasser, Himmelstein, and Woolhandler, the U.S. population was more likely to forgo medical care and have unmet healthcare needs compared to its Canadian

counterparts. Further, while both countries have health disparities on the basis of race, income, and immigrant status, these disparities were more extreme in the U.S.

Finally, a 2014 research study that studied 93 counties in the U.S. reported the relationship between education, sex, and race-related inequalities in four health outcomes: poor or fair health, poor physical health days, poor mental health days, and low birthweight (Asada, Whipp, Kindig, Billard, & Rudolph, 2014). The study found that "education contributed most to overall inequality in poor or fair health and poor physical and mental health days, but the contribution of race (white, black and other) was more pronounced for overall inequality in low birthweight (Asada et al., 2014)." Lastly, the study found that the healthiest group within each attribute of education, sex, and race were college graduated, male, and white, respectively. The results from this study and others highlight the influence socioeconomic statuses such as race, gender and education have on health outcomes. Consequently, this study includes race, gender, and education level as control variables (Asada et al., 2014; Lasser et al., 2006; Muramatsu, 2003; Wilkinson & Pickett, 2006).

The current body of literature on population health at the state level and small-area level provides different vantage points from which to investigate the association between population health and the determinants of health. It is equally important to analyze other determinants of population health, particularly since numerous studies have already focused on the relationship between socioeconomic status (SES) and population health. To date, the current literature has focused on SES and its impact on disease and chronic illnesses, but it fails to provide an overall picture on county-level health outcomes, specifically looking at the impact of health IT. These weaknesses have left a gap in the literature that is relevant in today's healthcare field, especially when so many resources have been dedicated to the development of the health IT infrastructure.

In fewer than ten years, the healthcare landscape in the U.S. has changed dramatically. With laws enacted to push hospitals and clinicians towards the adoption of health IT and the implications for LHDs, it is more important than ever to analyze the impact health IT has had on the health of the population. This study intends to provide an analysis on the effect of health IT on population health at the county level. Policy outputs can be tailored to meet specific population needs to improve health outcomes if more studies were conducted at a macro-level and on other determinants of population health. It is the intention of this study to promote actionable policies related to health IT adoption by LHDs to address the health disparities experienced by counties (Remington, Catlin, & Gennuso, 2015).

Defining Health Outcomes at the County Level

Since 2010, County Health Rankings have been produced on an annual basis by the University of Wisconsin Population Health Institute and the Robert Wood Johnson Foundation. The report ranks the health of over 3,000 U.S. counties in all states from the healthiest to the least healthy county within that state. The rankings are based on "a model that summarizes the overall health outcomes of each county, as well as the factors that contribute to health" (Remington et al., 2015). The report produces an *Overall Health Outcomes* composite ranking score in which it measures the health outcome of each individual county within each state. The population health of counties in this study comes from the 2016 County Health Rankings dataset.

Multiple methods are useful in measuring population health. Summary measures are one example. "Summary measures of population health combine information on mortality and non-fatal health outcomes to represent the health of a particular population as a single number"

(Murray, Salomon, & Mathers, 2000). Examples of the summary measures of population health include disability-free life expectancy (DFLE), disability-adjusted life years (DALYs), years of healthy life (YHL), quality-adjusted life expectancy (QALE), dementia-free life expectancy, health capital, premature death (years of potential life lost (YPLL)), and health-related quality of life (Murray et al., 2000; University of Wisconsin Population Health Institute, 2015). For purposes of this study, premature death as measured by YPLL and health-related quality of life (measure of morbidity) will be used to measure the health of the population at the county level. Further, these two measurements combine to form the *Overall Health Outcomes* score used to measure the health of the population at the county-level.

Overall Health Outcomes

Years of Potential Life Lost (YPLL)

The 2016 County Health Rankings dataset uses the age-adjusted YPLL rates to measure mortality across all counties, with a cutoff of 75 years of age. A cutoff age of 75 is commonly used, and since the average life expectancy for women and men was 81.2 years and 76.4 years, respectively, in 2014, using a cutoff age of 75 is justified for this study (Murphy, Kochanek, Xu, & Arias, 2015). Using other cut-off ages to measure YPLL is possible: 65 years of age and 85 years of age. Decreasing the cutoff to 65 years of age or increasing it to 85 years of age has minimal effect: an average rank change of 2.0 (Vila, Booske, Remington, 2006).

The 2016 County Health Rankings dataset justifies using a single measure of mortality rather than combining multiple measures of mortality, such as the United Health Foundation,

because the intention of the 2016 County Health Rankings dataset is to measure premature mortality rather than overall mortality. Premature mortality is understood to be potentially preventable. If more measures of mortality were included, it might capture areas with higher mortality rates due to old age and chronic illnesses in which policy outputs may offer no value (Vila et al., 2006). Thus, using only YPLL with a cutoff age of 75 combined with the measure of health-related quality of life produces a health outcome ranking that provides a comprehensive outlook for the health of each county.

Health-Related Quality of Life

Health-related quality of life (HRQoL) as defined by the CDC is "an individual's or group's perceived physical and mental health over time" (Centers for Disease Control and Prevention, 2000). Length of life is one indicator of health; however, the quality of those years also plays an important role in one's health. "HRQoL is a multi-dimensional concept that includes domains related to physical, mental, emotional, and social functioning" (County Health Rankings, 2016b). HRQoL is a measurement that focuses on health status and how that impacts one's quality of life. It is a self-reported measure, and although there may be potential self-reported bias it is one of the most frequently used health indicators in sociological health research (County Health Rankings, 2016b; Jylhä, 2009). The HRQoL measurement is derived from the 2016 County Health Rankings dataset, and the 2016 County Health Rankings dataset derived its HRQoL results from the CDC's Behavioral Risk Factor Surveillance Survey (BRFSS) questionnaire (County Health Rankings, 2016b). The HRQoL variable is composed of four

measures: poor or fair health, poor physical health days, poor mental health days, and low birth weight. In each of these four categories, a lower value indicates better health.

As mentioned earlier, for this study both measures of YPLL and of health-related quality of life are combined to create an *Overall Health Outcomes* score. A lower *Overall Health Outcomes* score indicates better health.

Age-Adjustment of Measures

To increase comparability of health measures between counties within each state, the 2016 County Health Rankings dataset used in this study adjusts for age for only some measures. The reason only some measures are age adjusted is because providers of the 2016 County Health Rankings dataset did not want to "mask the true burden of a health need in a county" (County Health Rankings, 2016a). Age-adjusted measures include premature death (YPLL), self-reported health, physically unhealthy days, and mentally unhealthy days (County Health Rankings, 2016a). Last, the providers of the 2016 County Health Rankings dataset collect a variety of national data sources to develop the report and the county rankings. Thus, each data source is standardized and adjusted accordingly.

Overview of Local Health Departments

Local health departments (or local public health agencies) have existed since the early twentieth century, and today there are over 3,000 local health departments in the nation. Public health activities and governance vary from state to state: some states' public health activities are

centralized at the state level, whereas other states' public health activities are controlled by counties or townships. The majority of local health departments serve only a single county; others serve multiple counties, or combined city–county health jurisdictions (Committee on Assuring the Health of the Public in the 21st Century, 2003).

LHDs are the foundation of the public health delivery system and perform many functions at the community level (Willard et al., 2012). All LHDs are different. Some may offer more services than others or perform different functions. Some of their many functions and responsibilities include immunization services (childhood and adult), screening of diseases and conditions (HIV/AIDs, other STDs, tuberculosis, cancer, diabetes, high blood pressure), treatment for communicable diseases, providing maternal and child healthcare (family planning, prenatal care, obstetrical care), primary care, oral health, behavioral/mental health services, substance abuse services, epidemiology and surveillance activities, tracking and controlling communicable disease outbreaks, preparation and response to natural disasters, communication outreach and education, provision of population-based services, and development of policies and recommendations to reduce the burden of chronic diseases, regulation, inspection and/or licensing activities, environment health activities and many other services (NACCHO, 2014; Willard et al., 2012).

Stable and sufficient funding provided to LHDs at both the federal and state levels allows LHDs to provide essential services to local communities. Thus, the more stable the funding, the more core services can be provided to the local community (Willard et al., 2012). LHD's funding can be based on the size, and the scope of services offered by the LHDs. Moreover, LHD's funding is also impacted by the type of governance structure, degree of urbanization and regional location. The ways in which LHDs are funded by the state and local communities also

demonstrates the types of public health services and initiatives they want the LHDs to focus on. Funding can come from many sources including federal, state, local, and clinical sources. LHDs that serve a population of 50,000 or less are considered a small LHD, medium sized LHDs serve between 50,000 – 499,999 and large LHDs serve populations that are over 500,000 (NACCHO, 2009, 2014). From the 2016 Profile Study, on average, small LHDs, LHDs with shared governance type, and rural LHDs receive more funding per capita from local, state and clinical sources. Regional location also impacts where LHDs receive funding. LHDs located in the Northeast and Midwest receive more funding per capita from local sources compared to LHDs in the South or West, while LHDs in the South receive more per capita from state funding and LHDs in the West receive more per capita from federal sources (NACCHO, 2009, 2014).

In a study looking at how the 2008–2010 economic recession impacted LHDs, researchers studied LHDs' ability to provide core services to their community. The study found that budget cuts negatively impacted LHDs' ability to appropriately "protect the public from preventable diseases, environmental hazards, and other threats to public health" (Willard et al., 2012). Thus, inadequate funding may impose significant barriers to the ability of LHDs to adopt health information technology, especially when funds are limited, only mission critical objectives will become the priority.

The performance of LHDs varies and largely depends on the population size served and how involved the LHD is within its local community (Erwin, 2008). Erwin (2008) performed a literature review and found 23 studies sought to analyze the performance of LHDs. What he found was that LHD performance was largely influenced by the size of the LHD, jurisdictional size, and funding mechanism. Larger LHDs, those that serve a larger population and those with

higher expenditures, tended to be the higher performing LHDs. Additional findings from Erwin's study on LHD performance and health outcomes were mixed. He found that some studies reported improved health status while other studies linked "higher performing LHDs with unfavorable health status and risk" (Erwin, 2008).

Health Information Technology Adoption

Electronic health records, health information exchanges, immunization registries, electronic disease reporting systems, and electronic lab reporting are examples of information technology used by LHDs. EHRs as defined by the Centers for Medicare and Medicaid (CMS) is an electronic version of a patient's medical history that includes patient demographics, clinical notes, medications, vital signs, immunizations, laboratory data, and any other data related to that patient's medical history (Centers for Medicare & Medicaid Services, 2012). EHRs can streamline clinical workflow and provide real-time access to a patient's medical files. Further, it has the ability to interface with clinical decision support systems, electronic prescribing, and many other clinical systems to support a patient's medical care.

Electronic health records (EHRs) have transformed the healthcare environment, and more recently EHRs have been emerging in LHDs as a technology that can be leveraged to increase the completeness of public health surveillance data by offering access to real-time data and improved efficiency (Birkhead, Klompas, & Shah, 2015; Paul et al., 2015). The HITECH Act has spurred the adoption of EHRs to approximately 97% of reporting hospitals and 83% of office-based physician practices (Adler-Milstein et al., 2014). The uptick in EHR adoption holds great potential for health information exchange between hospitals and LHDs.

Health information exchanges as defined by the ONC involves the access and sharing of electronic patient medical records to increase effectiveness and efficiency in the provision of healthcare services. Electronic sharing of patient information improves the quality of care received by patients, allows doctors timely access to medical records, contributes to the completeness of a patient's medical records and helps to reduce unnecessary costs associated with storing medical records in a paper format. Further, timely sharing of medical information reduces duplication of laboratory tests, readmissions, and medication errors, while improving patient diagnosis. Lastly, electronic transmission of patient records allows for the standardization of data which can then seamlessly integrate into a patient's EHR (Office of the National Coordinator for Health Information Technology (ONC), 2016).

The 2013 NACCHO Profile study reported that only 22% of LHDs have implemented EHRs, while only 13% have implemented HIEs. However, nearly half of LHDs have expressed their intent to implement these systems (NACCHO, 2014). The literature on LHD adoption of health IT has shown a slow adoption rate. In a study conducted with data from 2010 to 2013, the results showed a 2.7% increase in LHD EHR adoption, which suggested that only about 15% of LHDs adopted EHRs from 2010 to 2013. Interestingly, 8.5% of LHDs reported the discontinuation of EHR use (McCullough, Zimmerman, Bell, & Rodriguez, 2015). In another recent study on the implementation of EHRs and other informatics systems at LHDs (Shah, Leider et al., 2016), researchers studied the types of health information systems adopted by LHDs and the determinants of the likelihood of adoption. Of the 505 LHDs that responded, 69 (14%) LHDs had implemented HIEs, 416 (82%) LHDs had implemented an immunization registry, 368 (73%) had implemented an electronic disease reporting system, 245 (49%) had implemented electronic laboratory reporting, and 122 (24%) had implemented EHRs.

A study conducted in 2015 analyzed LHDs use, adoption, and discontinuation of EHRs. The study found a stronger association between a LHD utilizing EHR if sufficient funding is there as well as a stronger association in using EHRs if more clinical services are offered. Leadership and accreditation had less of an impact on the adoption of EHRs. Moreover, state-level governance was negatively associated with EHR use. As for LHD adoption of EHR, significant predictors in the adoption of EHR include the size of population, population density, and the provision of primary services by LHDs (McCullough et al., 2015). Similarly, a 2016 study found the driving factors in the adoption of information technology among LHDs included LHDs that provided a greater number of clinical services, greater per capita public health expenditures, employment of health IT specialists, population size, and executive leadership (Shah, Leider et al., 2016).

These studies revealed the characteristics and determinants in the adoption of health IT by LHDs, as affected by the size of the population served, the amount of clinical services provided by the LHD, and if the LHD receives adequate funding based on the services provided to meet the demands of the population served. However, the lack of theoretical guidance in these studies reveal a need for a theoretical approach in this area that focuses on the impact of health IT adoption on health outcomes.

Health Information Technology Adoption and Health Outcomes

With the substantial investment in healthcare information technology, it is imperative to analyze the value derived from health information technology. The Healthcare Information Management and Systems Society (HIMSS) is a cause-based, nonprofit organization with a

vision to promote "better health through information technology" (Healthcare Information Management and Systems Society, 2016a). Through their many initiatives, one project known as the Health IT Value Suite explores the values derived from health information technology based on their STEPS value framework. STEPS categorizes the value of health information technology into five categories: Satisfaction, Treatment/Clinical, Electronic Secure Data, Patient Engagement & Population Management, and Savings (Healthcare Information Management and Systems Society, 2016b). This section specifically looks at the Treatment/Clinical category of the value and shortfalls of health information technology on health outcomes.

To date, the available research on the benefits of health information technology such as an EHR is mixed. While most research analyzing the impact of health IT suggests improved clinical outcomes and increased patient satisfaction, other research finds no benefits from adopting health IT (Abramson et al., 2014; Kirsten, McKenzie & Clark, 2009; McCullough, Casey, Moscovice & Prasad, 2010). The research discussed in this section is in large part focused on clinical outcomes at the hospital level; however, these findings are still significant to LHDs as they describe the potential benefits or harm that may arise from implementing health IT.

Studies have shown benefits of health IT such as computerized physician order entry and clinical decision support tools in reducing adverse events such as medication errors, but one study showed the inability of health IT to reduce adverse events (AEs) related to procedural AEs, which are more strongly correlated with the technical skills and ability of the clinician (Abramson et al., 2014; Pham et al., 2012). Further, one study found that health IT value was context dependent, meaning the environment in which the health IT is used has implications on the value derived from using health IT. Health IT may find more value in a large health system

where care coordination is important for health outcomes and continuity of care. Another explanation for context-dependent health IT value is the extent and sophistication of the health IT adopted by hospitals and physician offices, which can influence the value of health IT.

Improved patient outcomes and reduction in adverse events can be realized through the use of health IT. The use of health IT depends not only on strong leadership but also on buy-in from all clinicians and staff, which is crucial to the implementation of health IT systems. EHRs have the ability to enhance patient safety and improve clinical outcomes through the use of various functions including alerts, checklists, predictive tools; clinical guidelines based on evidence-based practices; electronic prescribing leading to the reduction of medication errors and redundancy and generating performance dashboards and compliance reports (Silow-Carroll, Edwards, & Rodin, 2012). Moreover, the adoption of health IT has allowed for increased patient–physician communication, improved patient flow, elimination of duplicative tests, and the capturing of complete patient records (Silow-Carroll et al., 2012). As Blumenthal (2017) suggested, the treasure-trove of digital medical data collected and stored in EHRs has the potential to enhance population health, particularly the use of EHRs to provide useful information for identifying at-risk populations and to promote population health. The potential is there for both the public and private sectors to capitalize on the digital age of healthcare (Blumenthal, 2017).

Research Questions

This study aims to address the following research questions with respect to the nation's local health departments adoption of health IT:

1. Are there differences in the level of health information technology adoption across LHDs?
    a. What are the characteristics of the LHDs that adopt or do not adopt health information technology?
    b. What types of health information technology are most widely adopted by LHDs?
    c. Do the three institutional forces (coercive, mimetic, and normative) significantly impact the adoption of health information technology by LHDs?
2. What impact does LHDs adoption of health information technology have on population health and outcomes in their respective county?

Statement of Hypotheses

The study analyzes the impact of health IT (EHRs and HIEs) adoption amongst LHDs on county-level health outcomes. Using institutional theory as the driving mechanism of health IT adoption in LHDs, this study will add to the population health literature as it relates to how health IT impacts population health. The analysis will first seek to analyze the three isomorphic mechanisms —coercive, mimetic and normative—leading to the adoption of health IT by LHDs. Based on existing research and literature on institutional theory and isomorphism, it is expected

that the three isomorphic mechanisms will all be significant predictors of the adoption of EHRs and HIEs by LHDs at the county-level.

H_1: *Coercive isomorphic mechanism (i.e., the HITECH Act) is a statistically significant predictor of EHR implementation by LHDs.*

H_2: *Coercive isomorphic mechanism (i.e., the HITECH Act) is a statistically significant predictor of HIE implementation by LHDs.*

H_3: *Mimetic isomorphic mechanism (i.e., community health assessment) is a statistically significant predictor of EHR implementation by LHDs.*

H_4: *Mimetic isomorphic mechanism (i.e., community health assessments) is a statistically significant predictor of HIE implementation by LHDs.*

H_5: *Normative isomorphic mechanism (i.e., information system specialists) is a statistically significant predictor of EHR implementation by LHDs.*

H_6: *Normative isomorphic mechanism (i.e., information system specialists) is a statistically significant predictor of HIE implementation by LHDs.*

The second part of the analysis involves analyzing the relationship between the adoption of health IT and the impact it has on county-level health outcomes within the population. Based on the existing research and literature, it is expected that the adoption of health IT by LHDs will improve the health outcomes of population health within the counties.

H_7: *The adoption of health IT (i.e. EHR and HIE) by LHDs will lead to improved overall health outcomes at the county-level.*

CHAPTER FOUR – RESEARCH DESIGN AND MODELING APPROACH

This is a cross-sectional, quantitative study using secondary data from the National Association of County & City Health Officials (NACCHO), National Profile of Local Health Departments study from years 2008 and 2013, and the 2016 County Health Rankings data produced by the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. The 2016 County Health Rankings dataset uses the most recent data available for each measure at the time of the release. Generalized Estimating Equations (GEE), multiple linear regression (MLR), and logistic regression are the primary statistical methods used in this study to analyze the data. The following sections will outline the sample, sampling technique, sample size, unit of analysis, operationalization of variables, procedures of the study, and the analysis of the study.

Data Sources

The first set of secondary data analyzed in the study is from the National Association of County & City Health Officials (NACCHO) which provides the nation's leading and most complete source of data about LHDs in the U.S. Begun 27 years ago with the first publication of the Profile study published in 1989, the study was born out of the need to define LHDs (National Association of County & City Health Officials, 2009; NACCHO, 2014). Today, the Profile study is the most trusted source about LHDs, shedding light on the important responsibilities and challenges faced by LHDs. The Profile study provides comprehensive data on LHDs, and each Profile study contains standard themes that look at the structure, workforce, financing,

governance, activities, and services of LHDs and how these varies across the nation and the population served by the LHDs. However, with each publication of the Profile study, the research has been adapted to the changing healthcare landscape, with data collected on additional topics including accreditation, emergency preparedness, and health information technology (NACCHO, 2009). This study will use data from the NACCHO: the 2008 and 2013 National Profile of Local Health Departments studies, which is available to the public for a minor cost. From hereafter, the two NACCHO datasets will be referred to as the 2008 Profile Study and the 2013 Profile Study.

The second set of secondary data source analyzed in the study is the 2016 County Health Rankings produced by the collaborative efforts between the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute. The data are available to the public for free and can be downloaded directly from the County Health Rankings website at http://www.countyhealthrankings.org/. What began as an analysis of the counties in only the state of Wisconsin in 2003 and 2008 has since expanded to include all counties in the U.S. The County Health Rankings dataset provides a "population health checkup" of over 3,000 counties across the nation (Remington et al., 2015). The data source provides many measures of population health, including premature death and quality of life health outcome measures (University of Wisconsin Population Health Institute, 2015).

The components of the 2016 County Health Rankings dataset come from a compilation of nationally recognized data sources, including the National Center for Health Statistics, Behavioral Risk Factors Surveillance System, and National Center for Health Statistics—Natality files, among others. The intention of the annual County Health Rankings report is to

“mobilize action toward community health by stimulating interest among the media and policymakers” (Remington et al., 2015).

Measurement Instruments

The 2008 Profile Study (NACCHO, 2009) used a survey instrument that included a set of core questions plus three modules of supplemental questions. Module 2 contained survey questions pertaining to health IT and was used for this study. The questionnaire was piloted twice, in May and June of 2008, with the final questionnaire distributed on July 16, 2008. Most new questions, some pretested in a small-scale survey conducted in 2007, were placed in the three modules along with the set of core questions that had been used in previous Profile studies (NACCHO, 2009).

The 2013 Profile Study questionnaire included a set of core questions, plus two modules of supplemental questions, with new questions located in supplemental modules 1 and 2. The core questionnaire contained questions pertaining to community health assessment and planning and workforce, while module 2 contained questions pertaining to health IT. Module 2 was used for this study. Similarly, the set of core questions contained questions that had been used in previous Profile studies. A pilot study of the 2013 Profile questionnaire was conducted from October to November 2012, with the final questionnaire launched from January through March 2013 (NACCHO, 2014).

The 2016 County Health Rankings dataset did not use a survey instrument but rather compiled existing reliable and valid measures from other notable sources. Data reliability is a primary concern, especially for counties that are relatively small. The smaller the margin of

error for a measure, the stronger the reliability. The 2016 County Health Rankings dataset, taking into account the fact that the reliability of some measures was not ideal, used multiple measures to strengthen the reliability of certain measures. For example, when using a single measurement for morbidity, reliability may suffer. However, the 2016 County Health Rankings dataset used several measures of morbidity, so taken together the measurement of morbidity has greater reliability (County Health Rankings, 2016a).

Sampling

In the 2008 Profile Study (NACCHO, 2009) questionnaire, LHDs are randomly assigned to receive either only the core or the core plus one of the three modules. Stratified random sampling was used, with strata defined by the size of the population served by the LHD (NACCHO, 2009). The purpose of the module sampling process was to produce national estimates rather than state-level estimates. Populations were grouped into the following size categories:

- <25,000
- 25,000–49,999
- 50,000–99,000
- 100,000–249,999
- 250,000–499,999
- 500,000–999,999
- 1,000,000+

In the 2013 Profile Study (NACCHO, 2014) questionnaire LHDs are randomly assigned to receive either only the core or the core plus one of the two modules. Stratified random sampling was used, with strata defined by the size of the population served by the LHD as mentioned previously (NACCHO, 2014). The purpose of the module sampling process was to produce national estimates rather than state-level estimates.

For the 2016 County Health Rankings dataset, all counties in the U.S. are included in the study, as such no sampling method is required.

Unit of Analysis

The unit of analysis in this study is the U.S. county.

Sample Size

A total of 546 LHDs received the core plus module 2 questionnaire with an 87% (475 LHDs) response rate (NACCHO, 2009) for the 2008 Profile study. Two states, Hawaii and Rhode Island, were excluded from the study "because these state health departments operate on behalf of the local public health and have no sub-state units (NACCHO, 2009)." The final sample size included in this study is 100 observations from the 2008 Profile study dataset.

The 2013 Profile study population included 2,532 LHDs, but only 625 LHDs received the core plus module 2 questionnaire and yielded an 82% (505 LHDs) response rate (NACCHO, 2014). Two states, Hawaii and Rhode Island, were excluded from the study because of reasons

mentioned above. The final sample size included in this study is 505 observations from the 2013 Profile study dataset.

To analyze Hypothesis 1 and 2, the 2008 and 2013 Profile Study datasets were merged and only LHDs that completed the 2008 module 2 questionnaire and the 2013 module 2 questionnaire were included in the analysis, as it represented repeated observations. A total of 200 observations were included in the analysis.

The study population in the 2016 County Health Rankings dataset includes 3,142 counties (or county equivalents). States with county equivalents include Louisiana (parishes), Alaska (boroughs) and several major cities such as Baltimore and St. Louis. To analyze Hypothesis 7, the 2016 County Health Rankings dataset was merged with the 2013 Profile study dataset. The final sample size yielded a total of 433 observations for this study from the 2016 County Health Rankings dataset.

Operationalization of Variables

In the 2008 Profile Study, the LHDs' level of implementation of health IT was operationalized with the following question: "Indicate your LHD's level of awareness or activity for each of the following information technology areas." There were five IT areas of interest, but for purposes of this study, we are concerned with only EHRs and HIEs. The response categories for each health IT areas were (1) not aware, (2) aware, (3), investigating or have investigated, (4) planning to implement, and (5) have implemented. Response categories 1, 2, 3, and 4 were combined to reflect a level of "not implemented," which transformed the original multinomial variable into a dichotomized variable.

In the 2013 Profile Study, the LHDs' level of implementation of health IT was operationalized with the following question: "Indicate your LHD's level of activity for each of the following information technology areas." There were five IT areas of interest, but for purposes of this study we are concerned with only EHRs and HIEs. The response categories for each health IT areas were (1) no activity, (2) have investigated, (3), planning to implement, and (4) have implemented. Response categories 1, 2, and 3 were combined to reflect a level of "not implemented," which transformed the original multinomial variable into a dichotomized variable.

Table 2 lists the variables measured in the study along with their respective variable type and related survey questions or other data source. For this study, which is guided by the conceptual framework as outlined in the literature review, the first set of indicators measures the three isomorphic mechanisms of institutional theory and their impact on the adoption of health IT by LHDs. For example, to study the impact of coercive isomorphic mechanism, the adoption of EHRs and health information exchanges (HIEs) are the dependent variables, while the implementation of the HITECH Act, a form of coercive mechanism, is the independent variable. Second, to measure mimetic isomorphic mechanism, the completion of a community health assessment measure is analyzed for its ability to predict the likelihood of the adoption of EHRs and HIEs. Third, normative isomorphic mechanism is measured by employment of information system specialist indicator.

The second part of the analysis predicts how the adoption of health IT impacts the overall health outcomes within each county. Overall Health Outcomes is the dependent variable explained by the adoption of health IT.

Last, demographic and socioeconomic variables aggregated at the county level are included as control variables in the analysis for assessing the impact EHRs and HIEs have on the overall health outcomes within each county. The control variables are racial distribution (%African American, % Hispanic, % Non-Hispanic white, % Other (includes % American Indian and Alaskan Native, % Asian, % Native Hawaiian/Other Pacific Islander)), median household income, and percentage of rural population. Control variables in analyzing the implementation of EHRs and HIEs by LHDs include population size served, LHD governance classification, and revenue. These control variables were included in the analysis based on current literature and their potential effect on the dependent variables of interest. Complete survey questions are presented in Appendix A and B.

Table 2: Operationalization of Variables

Construct	Measure	Description	Survey item or data source
Adoption of Health IT	Level of activity with electronic health records	Dichotomous (0) Not implemented (1) Implemented	2008 Profile Study: q226 2013 Profile Study: m4q301
	Level of activity with health information exchange	Dichotomous (0) Not implemented (1) Implemented	2008 Profile Study: q227 2013 Profile Study: m4q302
Coercive Isomorphic Mechanism	Implementation of HITECH Act of 2009	Independent, dichotomous (0) Not implemented (1) Implemented	
Mimetic Isomorphic Mechanism	Completed a Community Health Assessment (CHA)	Independent, nominal (1) Yes, within the last three years (2) Yes, more than three but less than five years ago (3) Yes, five or more years ago (4) No, but plan to in the next year (5) No	2013 Profile Study: c7q147
Normative Isomorphic Mechanism	Employment of information system (IS) specialists?	Independent, dichotomous (0) No (1) Yes	2013 Profile Study: c5q50a
Overall Health Outcomes	Overall Health Outcomes (Combined YPLL and HRQoL)	Dependent, continuous	2016 County Health Rankings[1]
	YPLL	Age-adjusted YPLL rate per 100,000	
	HRQoL		
	• Poor or fair health	Percent of adults that report fair or poor health	
	• Poor physical health days	Average number of reported physically unhealthy days per month	
	• Poor mental health days	Average number of reported mentally unhealthy days per month	
	• Low birth weight	Percentage of births with low birth weight (<2500g)	

Construct	Measure	Description	Survey item or data source
Demographic and Socioeconomic Variables	Education level High School Graduation Rate % Some college	Control variable, continuous Percentage of ninth-grade cohort that graduates in four years Percentage of adults age 25-44 with some post-secondary education	2016 County Health Rankings[2]
	Race % African American % Hispanic % Non-Hispanic white % Other (% American Indian and Alaskan Native; % Asian; % Native Hawaiian/Other Pacific Islander)	Control variable, continuous	2016 County Health Rankings[3]
	Median household income	Control variable, continuous	2016 County Health Rankings[4]
	% Rural	Control variable, Continuous	2016 County Health Rankings[5]
	Population size served	Control variable, categorical, ordinal (1) <25,000 (2) 25,000 –49,999 (3) 50,000–99,999 (4) 100,000–249,999 (5) 250,000–499,999 (6) 500,000–999,999 (7) 1,000,000+	2008 Profile Study: N/A[6] 2013 Profile Study: c0popcat7
	LHD governance structure	Control variable, nominal (1) unit of state government (2) unit of local government (3) unit governed by both state and local authorities	2008 Profile Study: Govcat 2013 Profile Study: C0govcat
	Revenue (Funding)	Control variable, continuous	2008 Profile Study: q16 2013 Profile Study: c3q16

[1] Length of life (50%) source year 2011–2013; Quality of life (50%) source year 2007–2014
[2] Data source year 2010–2014
[3] Data source year 2014
[4] Data source year 2014
[5] Dara source year 2010
[6] Not included in the 2008 Profile dataset

Procedures

The 2008 and 2013 Profile study questionnaire was an electronic survey that was distributed via email to the top agency executive or, in some cases, a designated alternative in every LHD in the study universe. The email contained the link to the survey, which was customized to the LHD with identifying information specific to each LHD. Upon request, paper copies were available; only about 3% of the completed surveys were paper versions. The survey was available for approximately three months, and extensive efforts were made to increase the response rate. Non-respondents were followed-up by NACCHO staff and a nationwide group of Profile study advocates. Further, technical support was available through email and a telephone hotline (NACCHO, 2009, 2014).

The 2016 County Health Rankings dataset compiled data from existing databases. The variables used for this study from the 2016 County Health Ranking dataset came from the following datasets: The National Center for Health Statistics—Mortality files, Behavioral Risk Factor Surveillance System, EDFacts, American Community Survey, Small Area Income and Poverty Estimates, and Census Population Estimates. Each of these databases has its own method of data collection.

Data Analysis

Data were analyzed using several multivariate statistical tools, including generalized estimating equations (GEE), binomial logistic regression (logistic regression), and multiple linear regression (MLR). GEE allows for the examination of a categorical dependent variable and

repeated measures such as the pre-and post-implementation of the HITECH Act and its impact on the adoption of health IT by LHD (Wan, Ortiz, Du, Golden, 2017). The logistic regression model allows for the examination of a binary dependent variable (e.g., health IT implementation – yes/no) and "describes how the proportion of success depends on the explanatory (independent) variables" (Agresti & Finlay, 1997). Finally, MLR allows for the prediction of the adoption of health IT by LHDs and its impact on county-level health outcomes. MLR is selected for its predictive analysis ability between a continuous dependent variable and two or more independent variables (categorical or continuous). Further, respective goodness of fit models are used to determine how well our models fits the data available. The best fitting models were generated for each outcome measure or indicator at the county level.

Generalized Estimating Equations (GEE)

GEE is a quasi-likelihood, statistical method approach to longitudinal data sets comprising repeated observations of an outcome variable (categorical) and a set of independent variables (Wan et al., 2017; Zeger & Liang, 1986). GEE is appropriately used for describing "the marginal expectation of the outcome variable as a function of the covariates while accounting for the correlation among the repeated observations for a given subject" (Zeger & Liang, 1986). GEE requires few assumptions about the distribution of the outcome variable and is robust against a variety of not normally distributed dependent variables The quasi-likelihood information criterion (QIC) statistic reflects the overall fit of the model. Finally, test statistics and significance level are generated for each independent variable to allow for hypothesis testing with a p-value less than 0.05, signifying statistically significant results (Ballinger, 2004).

Multiple Regression

Multiple regression, a form of ordinary least squares regression, is a predictive analysis method that assesses the impact of one or more independent variables on a dependent variable. It requires the dependent variable to be continuous, while the independent variables can be either continuous (interval or ratio level) or dichotomous. Further, multiple regression allows the determination of the overall fit of the model and describes the proportion of the variation of the outcome variable as explained by the explanatory variables (Agresti & Finlay, 1997).

Statistical Inferences

In a multiple regression model, the multiple correlation coefficient (R), known as the Pearson correlation coefficient, describes the strength of the linear association between two variables. The R-Squared statistic indicates how well the predictor variables can explain the total variation in a given dependent variable, showing the proportion of the total variance in the dependent variable explained by the independent variables (Agresti & Finlay, 1997). The R-Squared statistic is a less conservative statistic and tends to be slightly biased upwards based on the sample population rather than the true population. Further, the bias is also affected by a small sample size. Because of the bias, the adjusted R-Squared provides a better estimate of the overall model fit that we would expect to see in the population (Agresti & Finlay, 1997).

The statistical significance (probability that the relationships happened by chance) of the overall model is represented by the *p*-value. A *p*-value less than .05 signifies statistical

significance with a 95% confidence interval that the "true value of the slope coefficient is between the lower and upper bounds" (Laerd Statistics, 2015b).

Assumptions

Six assumptions need to be met to justify the use of multiple regression. These include the following: (1) independence of observations, (2) linearity of the relationships, (3) homoscedasticity of residuals, (4) no multicollinearity, (5) no significant outliers, and (6) residuals are approximately normally distributed. Details for each assumption are provided below.

Independence of observations

MLR requires the errors of observations to be independent and unrelated. This is particularly a concern for repeated measures data. The Durbin-Watson statistics test for the lack of independence (errors are correlated). The Durbin-Watson value can range from 0 to 4; however, a value closest to 2 indicates the independence of errors (Laerd Statistics, 2015a).

Linearity of the relationships

For any MLR analysis, the assumption that: "(a) the independent variables collectively are linearly related to the dependent variable; and (b) each independent variable is linearly related to the dependent variable" needs to be met (Laerd Statistics, 2015b). A scatterplot offers

a simple visual depiction to determine whether the collective independent variables are linearly related to the dependent variable. To interpret the scatterplot for linearity, the residuals needs to form a horizontal band, which meets the assumption of linearity.

Partial regression plots offer visual depictions to support whether a linear relationship exists between the dependent variable and each of the independent variables. If both linearity assumptions are violated, it is possible to overcome the non-linear relationship by using transformation techniques (Laerd Statistics, 2015b).

Homoscedasticity of residuals

Homoscedasticity of residuals requires "that the residuals are equal for all values of the predicted dependent variable" (Laerd Statistics, 2015b). This means that there is "constant standard deviation throughout the range of values of the explanatory variables" (Agresti & Finlay, 1997). To check for violations of homoscedasticity, a scatterplot is generated that plots the studentized residuals against the unstandardized predicted values. To assume homoscedasticity, the data points on the scatterplot should exhibit no pattern (increasing, decreasing, fan-shaped) and will be approximately constantly spread. If such a pattern exists, then heteroscedasticity exists and remedial action will need to be taken to counteract the violation of homoscedasticity.

No multicollinearity

Multicollinearity describes the correlational relationship between the independent variables. It is important that the MLR model show no signs of multicollinearity, as highly correlated variables add little to the model in explaining the variances of the outcome (Agresti & Finlay, 1997). Prior to running a multiple regression analysis, multicollinearity can be tested in two stages to ensure that is it not a concern: inspection of the correlation coefficients in a correlation matrix and consulting the "Tolerance" and "VIF" values in the Coefficients table (Laerd Statistics, 2015b).

A correlation matrix is generated for the independent and control variables. Correlations greater than 0.7 indicate a strong correlation. In such a circumstance, one variable is removed from the analysis. The Tolerance and VIF can be found in the coefficients table generated in SPSS. Collinearity is indicated by a Tolerance value less than 0.1 and a VIF value greater than 10. If multicollinearity is an issue, the removal of the variable may be considered (Laerd Statistics, 2015b).

No significant outliers

"An outlier is an observation (data point) that does not follow the usual pattern of points (they are far away from their predicted value)" (Laerd Statistics, 2015b). Outliers can be detrimental to the overall fit of the model and can be removed. To detect outliers, SPSS generates the Casewise Diagnostics table of standardized residuals for each case. Any residual

value greater than +/- 3 standard deviations is treated as an outlier and may be removed from the analysis.

Normality

In running any MLR analysis, the residuals need to be normally distributed. Violation of this assumption compromises the validity of the analysis results and findings. There are two common methods to test for the assumption of normality: 1) generate a histogram with a superimposed normal curve and a P-P Plot or 2) generate a Normal Q-Q Plot of the studentized residuals (Laerd Statistics, 2015b).

In a review of the histogram, residuals may appear to be approximately normally distributed; however, the residuals may experience kurtosis or skewness, which impacts the normality of the residuals. Therefore, to confirm normality of the data, a review of the P-P Plot is performed. Normality of residuals is confirmed if the residuals align mostly along the diagonal line. The second method in testing for normality of the residuals is to generate a Q-Q Plot. Similarly, if the data points align closely to the diagonal line, the assumption of normality is not violated (Laerd Statistics, 2015b). Furthermore, MLR is robust against any deviations from normality.

Logistic Regression

Logistic regression is an analysis method that "predicts the probability that an observation falls into one of two categories of a dichotomous dependent variable" (Laerd

Statistics, 2015a) regressed on one or multiple independent variables (continuous or categorical). Unlike MLR, which has a quantitative outcome variable, logistic regression outcome variables are qualitative (discrete distribution) (Agresti & Finlay, 1997). Similarly, logistic regression allows the determination of the overall fit of the model and describes the proportion of the variation of the outcome variable as explained by the explanatory variables (Laerd Statistics, 2015a).

Statistical Inferences

Inferences drawn from a logistic regression model include the Wald statistic, which determines the statistical significance for each of the independent variables (Agresti & Finlay, 1997; Laerd Statistics, 2015a). A *p*-value less than .05 means the results are statistically significant and the null hypothesis is rejected. The Hosmer and Lemeshow goodness of fit test examines how poorly the model fits. We would want a *p*-value greater than .05, which signifies the model is not a poor fit (Laerd Statistics, 2015a). To determine how much of the variation in the dependent variable can be explained by the independent variables, we can consult the Cox & Snell R Square and the Nagelkerke R Square statistic. The Nagelkerke R Square statistic is preferred. Lastly, the odds ratio for each independent variable is used to understand the change in the odds for each one unit increase of the independent variable (Laerd Statistics, 2015a).

Assumptions

Four assumptions need to be met to justify the use of logistic regression. These include the following: (1) independence of observations, (2) linearity of the relationships, (3) no multicollinearity, and (4) no significant outliers. To avoid redundancy because these assumptions overlap with MLR, only the linearity of the relationships will be discussed in further detail as it is a slightly different analysis for logistic regression.

Linearity of the relationships

To meet the assumption of linearity in a logistic regression requires a linear relationship between the continuous independent variables and the logit transformation of the dependent variable (Laerd Statistics, 2015a). The Box-Tidwell procedure tests the linearity assumption in a logistic regression model. Once the independent variables are transformed into their natural logs, an interaction between the independent variable and its log is produced along with its *p*-value. After applying the Bonferroni correction based on all terms, a new *p*-value threshold is generated. To test for linearity, the *p*-values of the interaction terms need to be above the new alpha level (Laerd Statistics, 2015a).

Analytical Methods

Data Cleaning

To address missing observations in each of the datasets, Missing Value Analysis (MVA) in SPSS was performed and missing observations were imputed using multiple imputation (IBM Knowledge Center, 2017b).

Next, datasets had to be manually merged to reflect only variables of interest to the study. The next section provides details on how the datasets were merged.

Hypotheses One and Two

The 2008 Profile Study Module 2 and the 2013 Profile Study Module 2 datasets were merged because module 2 contained questions that pertained to the adoption of EHRs and HIEs. Further, only LHDs that completed the 2008 Profile Study Module 2 and the 2013 Profile Study Module 2 survey were kept in the dataset to reflect time series data for both 2008 and 2013 (pre- and post–HITECH Act implementation). Lastly, two variables were created, year and HITECH Act. After excluding variables that did not pertain to the study, the merged dataset contained a total of 7 variables.

Hypotheses Three, Four, Five and Six

The 2013 Profile Study was used to answer Hypotheses Three, Four, Five and Six. Only LHDs that received the module 2 survey were kept in the dataset because the variables of interest (EHR, HIE, Community Health Assessment) were found in the module 2 survey. After excluding variables that did not pertain to the study, the dataset contained a total of 9 variables.

Hypothesis Seven

To test Hypothesis Seven, the 2013 Profile Study was merged with the 2016 County Health Rankings dataset. The Profile 2013 dataset did not contain the five-digit Federal Information Processing Standard (FIPS) code which is used to identify county and county equivalents in the U.S. However, in a separate dataset from the NACCHO, the 2013 FIPS codes were provided and subsequently merged with the Profile 2013 dataset. The 2013 Profile dataset was then merged with the 2016 County Health Rankings dataset, and only LHDs that received the 2013 Profile Study Module 2 survey remained in the dataset. Lastly, LHDs with missing health outcomes data were deleted and not included in the final dataset.

To standardize the health outcomes variables, z scores were generated followed by the creation of a weighted composite variable to reflect the Overall Health Outcomes variable using principal component analysis, which is explained in further detail in the next section.

Principal Component Analysis

Principal component analysis (PCA) is a variable reduction technique that takes a large set of correlated variables and reduces it into a smaller set of artificial variables known as principal components, accounting for most of the variance in the original variables (Laerd Statistics, 2015c). The overall health outcome variable is composed of premature death as measured by YPLL, poor or fair health, poor physical health days, poor mental health days and low birthweight. SPSS determines the regression weights, multiply each observation by the respective weights and then sum the products. PCA enables the construction of the weighted overall health outcomes variable used in this study.

Analytical Frameworks

This section provides an integrated analytical framework to guide the specifications of the relationship between independent and dependent variables. It further illustrates how each of the 7 hypotheses will be empirically assessed and how each hypothesis was validated based upon criteria specific to the statistical test. Based on the conceptual framework, organizational context as explained by the three isomorphic mechanisms will directly influence organizational performance. As such, it is postulated that the three isomorphic mechanisms will drive the adoption of health IT by LHDs. Consequently, organizational performance then directly influences the health outcomes at the county level. Contextual variables such as governance structure, population size, socioeconomic status (race, education and income level), and LHD revenue are considered as control variables without including them as major hypotheses for this investigation. The following discussion describes each of the hypotheses and their respective statistical analyses.

Hypothesis 1: Coercive isomorphic mechanism (i.e., the HITECH Act) is a statistically significant predictor of EHR implementation by LHDs.

Coercive isomorphic mechanism is measured by the pre-and post-adoption of the HITECH Act, an independent, dichotomous variable. EHR is a dichotomous, dependent variable and is regressed against the independent variable (the HITECH Act) and three control variables (governance structure, population size served, and revenue). Generalized Estimating Equation (GEE) will be used to analyze this model, with an alpha level set at .05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is

less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

Hypothesis 2: Coercive isomorphic mechanism (i.e., the HITECH Act) is a statistically significant predictor of HIE implementation by LHDs.

Coercive isomorphic mechanism is measured by the pre-and post-adoption of the HITECH Act, an independent, dichotomous variable. HIE, is a dichotomous, dependent variable and is regressed against the independent variable (the HITECH Act) and three control variables (governance structure, population size served, and revenue). Generalized Estimating Equation (GEE) will be used to analyze this model, with an alpha level set at .05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

Hypothesis 3: Mimetic isomorphic mechanism (i.e., community health assessment) is a statistically significant predictor of EHR implementation by LHDs.

Mimetic isomorphic mechanism is measured by the completion of a community health assessment by the LHD, a categorical, independent variable. EHR, a categorical, dependent variable is regressed against the independent variable (CHA) and three control variables (governance structure, population size served, and revenue). Logistic regression was used to analyze this model, with an alpha level set at .05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

Hypothesis 4: Mimetic isomorphic mechanism (i.e., community health assessment) is a statistically significant predictor of HIE implementation by LHDs.

Mimetic isomorphic mechanism is measured by the completion of a community health assessment by the LHD, a categorical, independent variable. HIE, a categorical, dependent variable is regressed against the independent variable (CHA) and three control variables (governance structure, population size served, and revenue). Logistic regression was used to analyze this model, with an alpha level set at.05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is less than alpha at.05 or fail to reject the null if the *p*-value is greater than alpha at.05 (Hawkes & Marsh, 1993).

Hypothesis 5: Normative isomorphic mechanisms (i.e., information system specialists) is a statistically significant predictor of EHR implementation by LHDs.

Normative isomorphic mechanism is measured by the employment of information system specialists, which is a categorical, independent variable. EHR, a categorical, dependent variable is regressed against the independent variable (employed IS Specialists) and three control variables (governance structure, population size served, and revenue). Logistic regression was used to analyze this model, with an alpha level set at .05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

Hypothesis 6: Normative isomorphic mechanisms (i.e., information system specialists) is a statistically significant predictor of HIE implementation by LHDs.

Normative isomorphic mechanism is measured by the employment of information system specialists, which is a categorical, independent variable. HIE, a categorical, dependent variable is regressed against the independent variable (employed IS Specialists) and three control variables (governance structure, population size served, and revenue). Logistic regression was used to analyze this model, with an alpha level set at.05. The *p*-value describes the level of

statistical significance that could either reject the null hypothesis if the *p*-value is less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

Hypothesis 7: The adoption of health IT (i.e. EHR and HIE) by LHDs will lead to improved overall health outcomes at the county-level.

"Health outcomes" obtained by pooling the data of 2007-2013 together is the dependent variable. It is measured by the Overall Health Outcomes ranking score that combines both life expectancy and quality of life measures. The Overall Health Outcomes dependent variable is regressed against the independent variables of EHRs and HIEs, both of which are binary variables. Multiple linear regression was used to analyze this model, with an alpha level set at .05. The *p*-value, which describes the level of statistical significance, will either reject the null hypothesis if the *p*-value is less than alpha at .05 or fail to reject the null if the *p*-value is greater than alpha at .05 (Hawkes & Marsh, 1993).

CHAPTER FIVE – DATA ANALYSIS AND RESULTS

SPSS (IBM SPSS Statistics 24) was used for all data analysis in this study. This section includes assumptions testing for logistic and multiple regression, descriptive statistics, and the statistical analyses for GEE, logistic regression, and MLR.

Assumptions Testing

Multiple Linear Regression

Independence of Observations

The Durbin-Watson statistic tests for the lack of independence (errors are correlated). The Durbin-Watson value can range from 0 to 4; however, a value closest to 2 indicates the independence of errors (Laerd Statistics, 2015b). The Durbin-Watson statistic of 1.28 could indicate possible correlation between residuals. This may be an indication that counties that share similar sociodemographic characteristics may also have similar overall health outcomes. Further, some LHDs serve multiple counties, which could also impact the independence of observations. However, because the Durbin-Watson statistic is approximately 2, it is assumed that there is no correlation between residuals (Laerd Statistics, 2015b).

Linearity of Relationships and Homoscedasticity of residuals

The scatterplot is used to test both the assumptions of linearity and homoscedasticity. As demonstrated by Figure 2, the scatterplot, the residuals form a horizontal band, which indicates that the relationship between the dependent variable and the independent variables is likely to be linear. The assumption of homoscedasticity is also met because the spread of the residuals exhibits no clear pattern (increase of decrease of residuals), indicating the existence of homogeneity of variance (Laerd Statistics, 2015b).

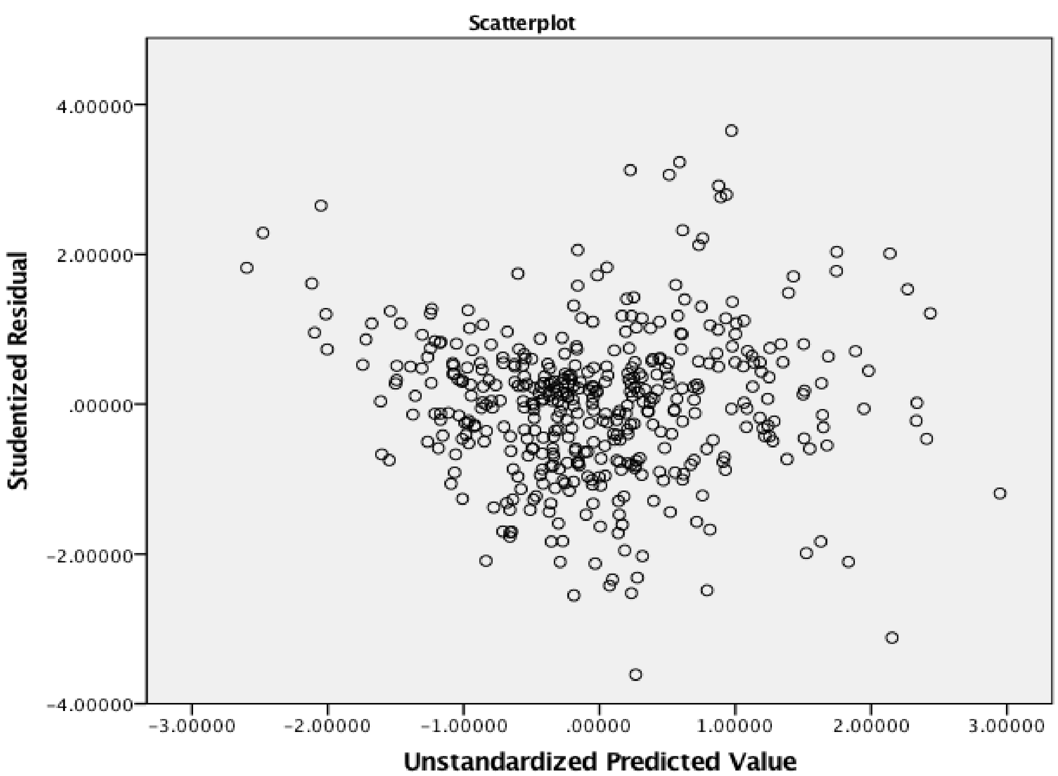

Figure 2: Scatterplot

Multicollinearity

A correlation matrix containing all independent and control variables was generated for the dependent variable of overall health outcomes to test the assumption of multicollinearity. Table 3 summarizes the correlation matrix output.

Any Pearson Correlation value greater than .7 indicates a strong intercorrelation between the two variables and may be problematic. The race variable, % non-Hispanic white control variable, was strongly correlated with the % African American and % Hispanic with correlation values at -.669 and -.669, respectively. Further, the Tolerance and VIF values for % non-Hispanic white was .002 and 468.632, respectively. Collinearity is indicated by a Tolerance value less than 0.1 and a VIF value greater than 10. Thus, the % non-Hispanic white control variable was strongly correlated with % African American and % Hispanic. Based on existing literature, socioeconomic disparities amongst minorities such as African Americans and Hispanics as compared to whites are much higher (Asada et al., 2014; Lasser et al., 2006; Muramatsu, 2003; Wilkinson & Pickett, 2006). With this empirical support, the control variable of % non-Hispanic white was removed from the model. Table 3 summarizes the correlation matrix output without the % non-Hispanic white control variable.

Table 3: Correlation Matrix of Variables

		Overall Health Outcomes	EHR	HIE	Median Household Income	% Other[1]	% African American	% Hispanic	% Some College	High School Graduation Rate	% Rural	State Governance	Local Governance	<25,000	25,000-49,999	50,000-99,999	100,00-249,999	250,000-499,999	500,000-999,999
Overall Health Outcomes	Pearson	1.000	-.182	.015	-.714	.053	.398	-.069	-.696	-.157	.224	.474	-.445	.087	.118	-.006	-.073	-.081	-.098
	Sig		.000	.380	.000	.135	.000	.077	.000	.001	.000	.000	.000	.035	.007	.449	.066	.046	.021
EHR	Pearson		1.000	.222	.131	.009	-.017	.098	.120	-.146	-.171	-.237	.131	-.117	-.014	-.010	.024	.044	.091
	Sig			.000	.003	.426	.359	.021	.006	.001	.000	.000	.003	.008	.384	.421	.307	.178	.029
HIE	Pearson			1.000	.013	.021	.067	-.023	.049	.036	-.059	.014	.012	-.048	-.015	.011	.016	.001	.099
	Sig				.393	.328	.082	.315	.155	.227	.111	.390	.400	.158	.375	.413	.369	.492	.020
Income	Pearson				1.000	.087	-.143	.179	.651	.151	-.410	-.241	.196	-.252	-.157	.000	.081	.163	.259
	Sig					.036	.001	.000	.000	.001	.000	.000	.000	.000	.001	.496	.047	.000	.000
% Other	Pearson					1.000	-.016	.190	.075	-.181	-.176	.046	-.011	-.112	-.096	.063	-.047	.067	.111
	Sig						.366	.000	.060	.000	.000	.167	.411	.010	.023	.094	.165	.082	.011
% African American	Pearson						1.000	.017	-.054	-.345	-.262	.258	-.274	-.148	-.130	-.031	.033	.154	.200
	Sig							.364	.129	.000	.000	.000	.000	.001	.003	.262	.249	.001	.000
% Hispanic	Pearson							1.000	-.037	-.226	-.426	-.142	.091	-.175	-.092	-.082	-.070	.088	.209
	Sig								.218	.000	.000	.002	.029	.000	.027	.043	.073	.033	.000
% Some College	Pearson								1.000	.008	-.463	-.307	.274	-.235	-.202	.011	.142	.192	.239
	Sig									.438	.000	.000	.000	.000	.000	.412	.001	.000	.000
High School Graduation Rate	Pearson									1.000	.236	.032	.071	.179	.137	-.027	.006	-.150	-.173
	Sig										.000	.254	.069	.000	.002	.284	.448	.001	.000
% Rural	Pearson										1.000	.192	-.090	.565	.170	.016	-.215	-.273	-.404
	Sig											.000	.031	.000	.000	.368	.000	.000	.000
State Governance	Pearson											1.000	-.783	.054	-.012	.001	.017	.067	-.133
	Sig												.000	.129	.401	.490	.361	.083	.003
Local Governance	Pearson												1.000	.008	.038	.032	-.079	-.108	.100
	Sig													.431	.218	.252	.050	.012	.019
<25,000	Pearson													1.000	-.303	-.263	-.242	-.202	-.197
	Sig														.000	.000	.000	.000	.000
25,000-49,999	Pearson														1.000	-.215	-.198	-.165	-.161
	Sig															.000	.000	.000	.000
50,000-99,999	Pearson															1.000	-.171	-.143	-.140
	Sig																.000	.001	.002
100,000-249,999	Pearson																1.000	-.132	-.128
	Sig																	.003	.004
250,000-499,999	Pearson																	1.000	-.107
	Sig																		.013
500,000-999,999	Pearson																		1.000

[1] % Other = Sum of %American Indian/Alaskan Native; %Asian; %Native Hawaiian/Other Pacific Islander

Two variables, household income and the percentage of completing some college coursework demonstrated correlation values at -.714 and -.696, respectively with the overall health outcomes dependent variable. Because multicollinearity is concerned with correlation amongst independent variables, this should not be problematic. Further, no variables had Tolerance values less than 0.1 and VIF values greater than 10, indicating multicollinearity is not an issue.

Normality

In visually inspecting the histogram, residuals appear to be approximately normally distributed. To confirm the normality of the data, a review of the P-P Plot was performed. Residuals aligned mostly along the diagonal line which confirmed the normality of residuals. The second method performed in testing for normality of the residuals was to generate a Q-Q Plot. The data points aligned closely to the diagonal line, which indicated that the assumption of normality is not violated (Laerd Statistics, 2015b).

Logistic Regression

Linearity of Relationships

The linearity of relationship assumption was met for the control variable revenue. Logistic regression requires only that continuous independent variables be linearly related to the logit transformation of the dependent variable.

Multicollinearity

A correlation matrix containing all independent and control variables was generated for each of the dependent variables (EHR and HIE) to test the assumption of multicollinearity. Tables 4 and 5 summarize the correlation matrix output for the dependent variables EHR and HIE, respectively.

Any Pearson Correlation value greater than .7 indicates a possible correlation and may be problematic. As shown in Table 4, there are no two variables with a Pearson Correlation greater than .7. The greatest correlation was between the population size served and employed IS specialist variables with a Pearson Correlation value of .486. Another statistical analysis to test for multicollinearity is the Tolerance and VIF values. Collinearity is indicated by a Tolerance value less than 0.1 and a VIF value greater than 10. No variables had a Tolerance value less than 0.1 and a VIF value greater than 10.

Table 4: Correlation Matrix of Independent and Control Variables for EHR

		EHR	Employed IS Specialist	Completed CHA	Population Size Served	Governance Structure	Total Revenue
EHR	Pearson	1.000	.168	-.094	.133	.213	.127
	Sig		.000	.017	.001	.000	.002
Employed IS Specialist	Pearson		1.000	-.128	.486	.268	.141
	Sig			.002	.000	.000	.001
Completed CHA	Pearson			1.000	-.119	-.193	.011
	Sig				.004	.000	.407
Population Size Served	Pearson				1.000	.103	.293
	Sig					.010	.000
Governance Structure	Pearson					1.000	-.102
	Sig						.011
Total Revenue	Pearson						1.000

Table 5 shows the correlation matrix that tests the assumption of multicollinearity with HIE as the dependent variable. As noted, there are no two variables with a Pearson Correlation greater than .7. The greatest correlation was between the population size served and employed IS specialist variables with a Pearson Correlation value of .486. Lastly, no variables had a Tolerance value less than 0.1 and a VIF value greater than 10.

Table 5: Correlation Matrix of Independent and Control Variables for HIE

		HIE	Employed IS Specialist	Completed CHA	Population Size Served	Governance Structure	Total Revenue
HIE	Pearson	1.000	.116	-.009	.005	-.004	.106
	Sig		.005	.424	.455	.468	.009
Employed IS Specialist	Pearson		1.000	-.128	.486	.268	.141
	Sig			.002	.000	.000	.001
Completed CHA	Pearson			1.000	-.119	-.193	.011
	Sig				.004	.000	.407
Population Size Served	Pearson				1.000	.103	.293
	Sig					.010	.000
Governance Structure	Pearson					1.000	-.102
	Sig						.011
Total Revenue	Pearson						1.000

Descriptive Statistics

Coercive Isomorphic Mechanism

As shown in Table 6, the number of LHDs adopting both EHRs and HIEs increased slightly from 2008 compared to 2013. Further, most LHD's governance structure is at the local level at 69% in 2008 and 66% in 2013, and just over 21% of LHDs served a population size of 500,000 or more in 2013. In the 2008 Profile Study, the only categories for governance structure were "state" and "local." The governance structure of "both" was added in the 2013 Profile Study. The 2008 Profile Study did not provide data on the population size served by the LHDs that received the module 2 questionnaire; thus, the 2013 population data were substituted for the

2008 data. Lastly, the wide range in revenue in both years as shown in Table 7 signifies the gaps in funding received by each LHD.

Table 6: Descriptive Statistics for Coercive Isomorphic Mechanism Measures—Categorical Variables

		Pre-HITECH Act (2008)		Post-HITECH Act (2013)	
Dimension	**Measure**	**N**	**Percent**	**N**	**Percent**
EHR	Not Implemented	79	79	72	72
	Implemented	21	21	28	28
HIE	Not Implemented	88	88	84	84
	Implemented	12	12	16	16
HITECH Act Implementation		100	100	100	100
Governance Structure	State	31	31	24	24
	Local	69	69	66	66
	Both	N/A	N/A	10	10
Population size served	<25,000	17	17	17	17
	25,000-49,999	13	13	13	13
	50,000-99,999	15	15	15	15
	100,000-249,999	20	20	20	20
	250,000-499,999	14	14	14	14
	500,000-999,999	14	14	14	14
	1,000,000+	7	7	7	7

Table 7: Descriptive Statistics for Coercive Isomorphic Mechanism Measures—Continuous Variable

	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
2008 Total Revenue	100	124,000	436,414,637	15,840,169.7	46,544,381.10
2013 Total Revenue	100	112,014.00	1,017,807,236	30,527,124.50	104,851,346

Quasi-likelihood Information Criterion (QIC)

“The Quasi-likelihood under Independence Model Criterion (QIC) can be used to help

you choose between two correlation structures, given a set of model terms" (IBM Knowledge Center, 2017a). The model with the smaller QIC value is the better fit. Two models were run for both EHR and HIE implementation as dependent variables. One model regressed the EHR variable against the "population size served by a LHD" independent variable, and the second model removed the "population size served by LHD" independent variable. As noted in Table 8 for the implementation of EHRs, the model without the "population size served by LHD" independent variable had a smaller QIC value of 213.725 compared to the QIC value of 215.557 (as shown in Table 9), which signifies a better model (IBM Knowledge Center, 2017).

Table 8: Quasi-likelihood Information Criterion (QIC) Analysis for EHR Implementation (without population size served by LHD)

	Value
Quasi Likelihood under Independence Model Criterion (QIC)	213.725

Table 9: Quasi-likelihood Information Criterion (QIC) Analysis for EHR Implementation (with population size served by LHD)

	Value
Quasi Likelihood under Independence Model Criterion (QIC)	215.557

As shown in Table 10, for the implementation of HIEs, the model without the "population size served by LHD" independent variable had a smaller QIC value of 164.548 compared to the QIC value of 169.221 (as shown in Table 11), which signifies a better model to the data.

Table 10: Quasi-likelihood Information Criterion (QIC) Analysis for HIE Implementation (without population size served by LHD)

	Value
Quasi Likelihood under Independence Model Criterion (QIC)	164.548

Table 11: Quasi-likelihood Information Criterion (QIC) Analysis for HIE Implementation (with population size served by LHD)

	Value
Quasi Likelihood under Independence Model Criterion (QIC)	169.221

Mimetic and Normative Isomorphic Mechanism

As shown in Table 12, more LHDs implemented EHRs compared to HIEs, 25.3% and 14.5% respectively. Next, 61.4% of LHDs indicated that a CHA was completed within the last three years, while 8.3% have never completed a CHA. With regards to the employment of IT specialists, 33.3% of LHDs had IS specialists on their team, while 66.7% did not employ any IS specialists. Further, most LHD's governance structure is at the local level at 72% and just over 12% of LHDs served a population size of 500,000 or more. Lastly, the wide range in revenue

ranging from $26,445 to $1,017,807,236 as shown in Table 13 reflects the large gaps in funding received by LHDs.

Table 12: Descriptive Statistics for Mimetic and Normative Isomorphic Mechanism Measures – Categorical Variables

Dimension	Measure	N	Percent
EHR	Not Implemented	377	74.7
	Implemented	128	25.3
HIE	Not Implemented	432	85.5
	Implemented	73	14.5
Completion of CHA	Yes, within the last three years	310	61.4
	Yes, more than three years ago	59	11.7
	Yes, five or more years ago	38	7.5
	No, but plan to in the next year	56	11.1
	No	42	8.3
Employed IS Specialists	No	337	66.7
	Yes	168	33.3
Governance Structure	State	101	20
	Local	363	71.9
	Both	41	8.1
Population size served by LHDs	<25,000	144	28.5
	25,000-49,999	102	20.2
	50,000-99,999	83	16.4
	100,000-249,999	69	13.7
	250,000-499,999	44	8.7
	500,000-999,999	44	8.7
	1,000,000+	19	3.8

Table 13: Descriptive Statistics for Mimetic and Normative Isomorphic Mechanism Measures—Continuous Variable

	N	Minimum	Maximum	Mean	Std. Deviation
Total Revenue	505	26,455.00	1,017,807,236	27,508,171.20	59,517,741.20

Hosmer and Lemeshow Test for EHR

To assess the adequacy of the model or how well the model fits, the Hosmer and Lemeshow analysis was performed. The Hosmer and Lemeshow "analyzes how poor the model is at predicting the categorical outcomes" (Laerd Statistics, 2015a). Therefore, we would want results to not be statistically significant.

Tables 14 and 15 provides the results for the Hosmer and Lemeshow analysis with EHR and HIE as the dependent variable, respectively, to test the mimetic isomorphic mechanism. With *p*-values above .05, which is not statistically significant, both models are not a poor fit.

Table 14: Hosmer and Lemeshow Goodness-of-Fit Analysis for Mimetic Isomorphic Mechanism Impact on EHR Implementation

Step	Chi-square	df	Sig.
1	14.902	8	.061

Table 15: Hosmer and Lemeshow Goodness-of-Fit Analysis for Mimetic Isomorphic Mechanism Impact on HIE Implementation

Step	Chi-square	df	Sig.
1	10.297	8	.245

Tables 16 and 17 provide the results for the Hosmer and Lemeshow analysis with EHR and HIE as the dependent variable, respectively, to test the normative isomorphic mechanism. With *p*-values above .05, which is not statistically significant, the two models generate comparable results or little differences are observed.

Table 16: Hosmer and Lemeshow Goodness-of-Fit Analysis for Normative Isomorphic Mechanism Impact on EHR Implementation

Step	Chi-square	df	Sig.
1	12.526	8	.129

Table 17: Hosmer and Lemeshow Goodness-of-Fit Analysis for Normative Isomorphic Mechanism Impact on HIE Implementation

Step	Chi-square	df	Sig.
1	7.338	8	.501

Overall Health Outcomes

Table 18 summarizes the mean, standard deviation, and ranges of the continuous variables in the analysis of health IT implementation and its impact on the overall health outcomes at the county level. The average household income per county is approximately \$49,388, while the average population size is approximately 236,131. Averages of 8% and 9% of African Americans and Hispanics, respectively, represent the demographics of the counties, while the percentage of American Indians, Asians, and Native Hawaiian on average made up less than 2% of the county population. Finally, 46% of the county population live in rural areas, and on average over 50% of the population have completed some college coursework.

Table 18: Descriptive Statistics of Counties for Continuous Variables

	Minimum	Maximum	Mean	Std. Deviation
Household Income	25,413.00	122,641.00	49,388.14	12,866.44
Population Size	1,117	10,116,705	236,131.91	681,116.83
% African American	.105	74.49	7.96	12.85
% American Indian/Alaskan Native	.089	73.50	1.81	5.87
% Asian	.078	28.86	1.89	2.80
% Native Hawaiian/Other Pacific Islander	.000	1.62	.12	.19
% Hispanic	.436	81.22	8.98	11.92
% Some College	22.219	86.12	58.40	11.55
% Rural	.000	100.00	46.39	32.60
Graduation Rate	46.354	101.26	84.96	8.31

Table 19 provides the descriptive statistics for the categorical variables. As shown in Table 19, over 70% of LHDs within each county have not implemented an EHR or HIE. Sixty-eight percent of LHDs' governance structure is at the local level, and the vast majority (over 70%) of LHDs serve populations of 250,000 and under.

Table 19: Descriptive Statistics of Counties for Categorical Variables

Dimension	**Measure**	**N**	**Percent**
EHR	Not Implemented	326	75.3
	Implemented	107	24.7
HIE	Not Implemented	375	86.6
	Implemented	58	13.4
LHD Governance Structure	State	95	21.9
	Local	297	68.6
	Both	41	9.5
Population size served by LHDs	<25,000	117	27
	25,000-49,999	86	19.9
	50,000-99,999	68	15.7
	100,000-249,999	59	13.6
	250,000-499,999	43	9.9
	500,000-999,999	41	9.5
	1,000,000+	19	4.4

Table 20 provides an overview of the number of counties in each state that are represented in the analysis. Illinois, Missouri, Ohio, and Tennessee had over 20 counties included in the analysis. Some states, including Alaska, Delaware, and Nevada, had only one included

Table 20: Descriptive Statistics for Number of Counties Represented

State	Number of Counties	Percent	State	Number of Counties	Percent
Alabama	14	3.2	Mississippi	2	.5
Alaska	1	.2	Missouri	23	5.3
Arizona	3	.7	Montana	8	1.8
Arkansas	17	3.9	Nebraska	6	1.4
California	15	3.5	Nevada	1	.2
Colorado	14	3.2	New Jersey	7	1.6
Delaware	1	.2	New York	11	2.5
District of Columbia	1	.2	North Carolina	17	3.9
Florida	17	3.9	North Dakota	6	1.4
Georgia	5	1.2	Ohio	24	5.5
Idaho	2	.5	Oklahoma	18	4.2
Illinois	23	5.3	Oregon	7	1.6
Indiana	17	3.9	Pennsylvania	6	1.4
Iowa	16	3.7	South Dakota	4	.9
Kansas	12	2.8	Tennessee	22	5.1
Kentucky	9	2.1	Texas	16	3.7
Louisiana	3	.7	Utah	6	1.4
Maine	3	.7	Virginia	9	2.1
Maryland	6	1.4	Washington	13	3.0
Massachusetts	2	.5	West Virginia	11	2.5
Michigan	5	1.2	Wisconsin	15	3.5
Minnesota	10	2.3	Wyoming	5	1.2
			Total	433	100.0

Goodness of Fit

The adjusted R-Squared value of .738 indicates that 73.8% of the variance in the dependent variable can be explained by the model. Essentially, the adjusted R-Squared assesses the overall model fit that we would expect in the population.

GEE Analysis Results for Coercive Isomorphic Mechanism

H_1: Coercive isomorphic mechanism (HITECH Act) is a statistically significant predictor of EHR implementation by LHDs.

The first hypothesis predicts that the implementation of the HITECH Act, a form of coercive mechanism, is a statistically significant predictor of LHDs' implementing EHRs. The QIC statistics indicated that the better model is without the "population size served" independent variable. Table 21 provides the parameter estimates results from the GEE analysis. With a significance level of .05 as the threshold for statistically significant results, only state governance structure was statistically significant with a *p*-value of .000. The implementation of the HITECH Act was found not to be statistically significant. Thus, Hypothesis 1 is not supported by the data.

Table 21: Parameter Estimates for EHR Implementation

			95% Wald Confidence Interval		Hypothesis Test		
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.
Intercept	-3.53	.8099	-5.118	-1.943	1	1	.000
HITECH Act Not Implemented	-.013	.2791	-.560	.534	.002	1	.963
State Governance Structure	2.579	.7550	1.099	4.059	11.667	1	.001**
Local Governance Structure	.832	.6581	-.458	2.122	1.599	1	.206
LHD Annual Revenue	5.281E-9	3.0848E-9	-7.649E-10	1.133E-8	2.931	1	.087

N=200

**Indicates statistical significance at $p \leq .05$

H_2: Coercive isomorphic mechanism (HITECH Act) is a statistically significant predictor of HIE implementation by LHDs.

The second hypothesis predicts that the implementation of the HITECH Act, a form of coercive mechanism, is a statistically significant predictor of LHDs' implementing HIEs. The QIC statistic indicated that the better model is without the "population size served" independent variable. Table 22 provides the parameter estimates results from the GEE analysis. With a significance level of .05 as the threshold for statistically significant results, only LHD annual revenue was statistically significant, with a *p*-value of .003. The implementation of the HITECH Act was found to be not statistically significant. Hypothesis 2 is not supported.

Table 22: Parameter Estimates for HIE Implementation

Parameter	B	Std. Error	95% Wald Confidence Interval Lower	95% Wald Confidence Interval Upper	Hypothesis Test Wald Chi-Square	Hypothesis Test df	Hypothesis Test Sig.
Intercept	1.849	1.1894	-.483	4.180	2.416	1	.120
HITECH Act Not Implemented	.-.055	.3837	-.807	.697	.021	1	.886
State Governance Structure	.240	1.1556	-2.025	2.505	.043	1	.836
Local Governance Structure	.383	1.1281	-1.828	2.594	.115	1	.734
LHD Annual Revenue	-9.966E-8	3.5035E-9	-1.683E-8	-3.099E-9	8.092	1	.004**

N=200

**Indicates statistical significance at $p \leq .05$

Logistic Regression Analysis Results for Mimetic Isomorphic Mechanism

H_3: Mimetic isomorphic mechanism (community health assessment) is a statistically significant predictor of EHR implementation by LHDs.

The third hypothesis predicts that the completion of a community health assessment, a form of mimetic isomorphic mechanism, is a statistically significant predictor of EHR implementation by LHDs. The control variable of population size served by LHD was removed from the model because it was not found to be statistically significant. The results are displayed in Table 23.

Table 23: Variables in the Equation Output for EHR Implementation

	B	S.E.	Wald	df	Sig.	EXP(B)	95% C.I. for EXP(B)	
							Lower	Upper
Constant	-2.919	.457	40.767	1	.000	.054		
Completion CHA - within 3 years	-.026	.334	.006	1	.937	.974	.506	1.874
Completion CHA - more than 3 years but less than 5 years	-1.349	.625	4.660	1	.031**	.260	.076	.883
Completion CHA - 5 or more years ago	-.264	.375	.495	1	.482	.768	.369	1.601
Completion CHA - No, but plan to in the next year	-.168	.417	.162	1	.688	.846	.373	1.915
Governance Structure - State	1.898	.438	18.775	1	.000**	6.676	2.828	15.756
Governance Structure - Local	2.355	.536	19.271	1	.000**	10.535	3.682	30.146
Total Revenue	.000	.000	11.729	1	.001**	1.000	1.000	1.000

N=505

**Indicates statistical significance at $p \leq .05$

With a significance level of .05 as the threshold for statistically significant results, completion of CHA between 3 to 5 years with a *p*-value of .031 was statistically significant while controlling for governance structure and revenue. State governance structure with a *p*-value of .000, local governance structure with a *p*-value of .000, and revenue with a *p*-value of .001 were all found to be statistically significant as well.

The Cox & Snell R square statistic and the Nagelkerke R square statistic determine how much of the variation in the dependent variable can be explained by the independent variables. Because the Nagelkerke R Square statistics is preferred, that is what was used. The Nagelkerke R square statistic of .141 indicated that 14.1% of the variation in the dependent variable was explained by the model.

The B coefficient predicts the probability of an event occurring, essentially the "change in the log odds that occur for a one-unit change in an independent variable when all other independent variables are kept constant" (Laerd Statistics, 2015a). However, because it is not inherently intuitive to consult the B coefficient, the Exp(B) represents the odds ratio for each of the independent variables. The completion of CHA between three to five years was found to be statistically significant. The odds ratio of .26 indicates that the odds of implementing EHRs by LHDs is .26 times less for LHDs that have completed the CHA between three to five years compared to LHDs that have never completed a CHA. Hypothesis 3 is not supported.

H_4: Mimetic isomorphic mechanism (community health assessments) is a statistically significant predictor of HIE implementation by LHDs.

The fourth hypothesis predicts that the completion of a community health assessment, a form of mimetic isomorphic mechanism, is a statistically significant predictor of HIE implementation by LHDs. The results are displayed in Table 24.

Table 24: Variables in the Equation Output for HIE Implementation

	B	S.E.	Wald	df	Sig.	EXP(B)	95% C.I. for EXP(B) Lower	Upper
Constant	-2.335	.431	29.323	1	.000	.097		
Completed CHA - within 3 years	.603	.366	2.723	1	.099	1.828	.893	3.742
Completed CHA - more than 3 years by less than 5 years	-.120	.519	.054	1	.817	.887	.321	2.453
Completed CHA - 5 or more years ago	.159	.419	.144	1	.704	1.172	.516	2.666
Completed CHA - No, but plan to in the next year	-.431	.562	.588	1	.443	.650	.216	1.956
Governance Structure- State	.305	.355	.738	1	.390	1.357	.676	2.721
Governance Structure- Local	-.106	.629	.028	1	.867	.900	.262	3.087
Total Revenue	.000	.000	7.296	1	.007**	1.000	1.000	1.000
<25,000	.159	.376	.180	1	.672	1.173	.561	2.449
25,000 –49,999	.278	.388	.512	1	.474	1.320	.617	2.825
50,000–99,999	-.141	.459	.094	1	.759	.869	.353	2.136
100,000 – 249,000	-.144	.547	.070	1	.792	.866	.296	2.528
250,000-499,999	.394	.464	.721	1	.396	1.483	.597	3.683
500,000-999,999	-4.397	2.748	2.560	1	.110	.012	.000	2.690

N=505

**Indicates statistical significance at $p \leq .05$

With a significance level of .05 as the threshold for statistically significant results, the independent variable of completion of CHA was not found to be statistically significant. The control variable of revenue was found to be statistically significant with a *p*-value of .007.

A Nagelkerke R square statistic of .071 indicates that 7.1% of the variation in the dependent variable is explained by the model. Hypothesis 4 is not supported.

Logistic Regression Analysis Results for Normative Isomorphic Mechanism

H_5: Normative isomorphic mechanisms (information system specialists) is a statistically significant predictor of EHR implementation by LHDs.

The fifth hypothesis predicts that the employment of IS specialists, a form of normative isomorphic mechanism, is a statistically significant predictor of EHR implementation by LHDs. The control variable of population size served by LHD was removed from the model because it was not found to be statistically significant. The results are displayed in Table 25.

Table 25: Variables in the Equation Output for EHR Implementation

							95% C.I. for EXP(B)	
	B	S.E.	Wald	df	Sig.	EXP(B)	Lower	Upper
Constant	-3.208	.445	52.052	1	.000	.040		
Employed IS Specialist - Yes	.564	.238	5.630	1	.018**	1.757	1.103	2.799
Total Revenue	.000	.000	9.087	1	.003**	1.000	1.000	1.000
Governance Structure - State	1.925	.434	19.656	1	.000**	6.854	2.927	16.050
Governance Structure - Local	2.072	.551	14.148	1	.000**	7.944	2.698	23.390

N=505

**Indicates statistical significance at $p \leq .05$

With a significance level of.05 as the threshold for statistically significant results, employment of IS specialist with a *p*-value of .018 was statistically significant while controlling for governance structure and revenue. State governance structure with a *p*-value of .000, local governance structure with a *p*-value of .000, and revenue with a *p*-value of .003 were all found to be statistically significant as well.

A Nagelkerke R square statistic of .138 indicated that 13.8% of the variation in the dependent variable was explained by the model.

The employment of IS specialist was found to be statistically significant. The odds ratio of 1.757 indicates that the odds of implementing EHRs by LHDs is 1.757 times greater for LHDs that employ IS specialists compared to LHDs that do not employ IS specialists. Hypothesis 5 is supported.

H_6: Normative isomorphic mechanisms (information system specialists) is a statistically significant predictor of HIE implementation by LHDs.

The sixth hypothesis predicts that the employment of IS specialists, a form of normative isomorphic mechanism, is a statistically significant predictor of HIE implementation by LHDs. The control variable of population size served by LHD and governance structure was removed from the model because they were not found to be statistically significant. The results are displayed in Table 26.

Table 26: Variables in the Equation Output for HIE Implementation

							95% C.I. for EXP(B)	
	B	S.E.	Wald	df	Sig.	EXP(B)	Lower	Upper
Constant	-2.102	.177	141.184	1	.00	.12		
Total Revenue	.000	.000	2.328	1	.12	1.00	1.00	1.00
Employed IS Specialist - Yes	.602	.261	5.332	1	.02**	1.82	1.09	3.04

N=505

**Indicates statistical significance at $p \leq .05$

With a significance level of .05 as the threshold for statistically significant results, employed IS specialist with a p-value of .021 was statistically significant while controlling for revenue. After removing population size served and governance structure, revenue with a *p*-value of .127 was not found to be statistically significant.

A Nagelkerke R square statistic of .033 indicated that 3.3% of the variation in the dependent variable was explained by the model.

The employment of IS specialist was found to be statistically significant. The odds ratio of 1.825 indicates that the odds of implementing HIEs by LHDs is 1.825 times greater for LHDs that employ IS specialists compared to LHDs that do not employ IS specialists. Hypothesis 6 is supported.

Multiple Linear Regression Analysis Results for the Impact of Health IT on Health Outcomes

Hypothesis 7: The adoption of health IT (i.e. EHR and HIE) by LHDs will lead to improved overall health outcomes at the county-level.

The seventh hypothesis predicts that he adoption of health IT (i.e. EHR and HIE) by LHDs will lead to improved overall health outcomes at the county-level. The results are displayed in Table 27.

Table 27: Overall Health Outcomes Score Regressed Against Independent and Control Variables

	Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
Constant	3.522	.368		9.584	.000	2.800	4.245					
EHR	-.130	.060	-.056	-2.167	.031**	-.247	-.012	-.182	-.106	-.052	.850	1.177
HIE	.062	.072	.022	.868	.386	-.079	.203	.015	.043	.021	.916	1.092
Household Income	-3.267E-5	.000	-.419	-11.908	.000**	.000	.000	-.714	-.505	-.284	.458	2.185
% African American	.018	.002	.234	8.032	.000**	.014	.023	.398	.367	.191	.668	1.497
% Hispanic	-.005	.003	-.054	-1.717	.087	-.010	.001	-.069	-.084	-.041	.576	1.736
%Other	.017	.004	.109	4.306	.000**	.009	.025	.053	.207	.103	.888	1.126
% Some College	-.035	.003	-.408	-11.030	.000**	-.041	-.029	-.696	-.476	-.263	.414	2.416
Graduation Rate	.003	.003	.027	.932	.352	-.004	.010	-.157	.046	.022	.683	1.465
% Rural	-.003	.001	-.096	-2.279	.023**	-.005	.000	.224	-.111	-.054	.320	3.127
State Gov	.233	.099	.097	2.351	.019**	.038	.428	.474	.115	.056	.333	2.999
Local Gov	-.248	.085	-.116	-2.910	.004**	-.416	-.081	-.445	-.141	-.069	.358	2.790
<25,000	-.090	.153	-.040	-.588	.557	-.390	.210	.087	-.029	-.014	.122	8.188
25,000-49,999	.016	.147	.006	.109	.913	-.273	.305	.118	.005	.003	.163	6.138
50,000-99,999	-.032	.144	-.012	-.220	.826	-.315	.252	-.006	-.011	-.005	.204	4.900
100,000-249,999	-.073	.143	-.025	-.513	.608	-.355	.208	-.073	-.025	-.012	.233	4.294
250,000-499,999	-.064	.143	-.019	-.447	.655	-.345	.217	-.081	-.022	-.011	.307	3.252
500,000-999,999	.137	.142	.040	.960	.338	-.143	.417	-.098	.047	.023	.323	3.096

N = 433

**Indicates statistical significance at p≤.05

Other = Sum of %American Indian/Alaskan Native; %Asian; %Native Hawaiian/Other Pacific Islander

A beta weight is a measure of strength and direction of the independent variables on a dependent variable. The standardized beta weights also allow direct comparisons to other independent variables. A -.056 beta weight for EHR indicates a small negative effect on overall health outcomes. Consequently, a negative value indicates that increases in the implementation of EHRs is correlated with lower overall health outcomes scores, which translates to improved overall population health.

The implementation of EHRs was found to be statistically significant with a *p*-value of .034, while controlling for governance structure, household income, % African American, % Other (%American Indian/Alaskan Native; %Asian; %Native Hawaiian/Other Pacific Islander), % Hispanic, % some college courses completed, and % rural areas. However, the implementation of HIEs was not statistically significant, with a *p*-value of .430. Hypothesis 7 was only partially supported.

Summary of Hypotheses Testing Results

The aims of this study were twofold. First, guided from a theoretical perspective under institutional theory, the theory postulates that organizations undergo changes driven by three types of isomorphic mechanisms: coercion, mimetic, and normative. As legislations and the healthcare environment increasingly turn to the implementation of health IT as the solution to strengthen and improve our healthcare system, it is prudent to understand what types of isomorphic mechanisms are most effective in generating change. The second part of this study sought to analyze the effectiveness of the implementation of health IT and its impact on population health. Specifically, it sought to understand whether the adoption of EHRs or HIEs

has any direct impact on population health. Table 28 summarizes the hypotheses and results from the hypothesis testing.

Table 28: Summary of Hypothesis Testing Results

	Hypothesis	Results
H_1	Coercive isomorphic mechanism (HITECH Act) is a statistically significant predictor of EHR implementation by LHDs	Not supported
H_2	Coercive isomorphic mechanism (HITECH Act) is a statistically significant predictor of HIE implementation by LHDs	Not supported
H_3	Mimetic isomorphic mechanism (community health assessment) is a statistically significant predictor of EHR implementation by LHDs	Not supported
H_4	Mimetic isomorphic mechanism (community health assessments) is a statistically significant predictor of HIE implementation by LHDs	Not supported
H_5	**H_5: Normative isomorphic mechanisms (information system specialists) is a statistically significant predictor of EHR implementation by LHDs**	**Supported**
H_6	**H_6: Normative isomorphic mechanisms (information system specialists) is a statistically significant predictor of HIE implementation by LHDs**	**Supported**
H_7	**The adoption of health IT (i.e. EHR and HIE) by LHDs will lead to improved overall health outcomes at the county-level.**	**Partially supported**

Coercive isomorphic mechanism in the form of the HITECH Act was not a significant predictor of the implementation of EHRs and HIEs. Mimetic isomorphic mechanism as measured by the completion of a CHA was not a statistically significant predictor of EHR or HIE implementation. Normative isomorphic mechanisms was found to be statistically significant in driving the implementation of EHRs and HIEs by LHDs. Lastly, EHRs were found to be

statistically significant on improving the overall health of the population, while HIEs were not found to be a significant predictor of health outcomes.

The purpose of this study was to provide a theoretical approach in understanding the driving forces of health IT implementation by LHDs. Further, this study intended to analyze the impact of health IT (EHR and HIE) on health outcomes. While the study used one independent variable as the measure for each of the three isomorphic mechanisms: coercive, mimetic, and normative, the independent variables selected truly reflect the three isomorphic mechanisms, providing evidence on how to effect change in LHDs. Additionally, even though health IT comes in many forms, EHRs and HIEs are becoming ubiquitous in the healthcare environment, which is why the study analyzed the impact of EHRs and HIEs on population health. What the study found was that not all health IT systems significantly impact the health of the population. Implementation of EHRs was a statistically significant predictor for improving health outcomes; however, the use of HIEs was not found to be statistically significant.

CHAPTER SIX – DISCUSSION AND CONCLUSION

This study was undertaken to explore the isomorphic mechanisms in the adoption of health IT by LHDs and how the adoption of health IT have impacted population health at the county level. In this chapter, a discussion of the findings from this study will be presented. First, results from the analysis will be discussed, followed by theoretical and practical implications. The section concludes with limitations, directions for future research, and concluding remarks.

Coercive Isomorphic Mechanism (HITECH Act)

Coercive isomorphic mechanism was the only mechanism that was not a statistically significant predictor in either of the implementations of EHRs or HIEs by LHDs. The study used the implementation of the HITECH Act in measuring coercive mechanism. Coercive mechanism through the enactment of laws and mandates is a driving force for organizational change. As federal laws are uniform across state and county borders, variations in the adoption of EHRs and HIEs at the county level may not be observed, which is not to say that the coercive forces have no influence on the adoption of EHRs and HIEs. Presumably, the HITECH Act did not provide the impetus needed to drive the implementation of EHRs or HIEs by LHDs. State regulations may have more of an impact on the adoption of EHRs and HIEs.

The findings also show that although the adoption of EHRs and HIEs did increase from 2008 to 2013, the increase was very minor. The HITECH Act was targeted at physicians and hospitals and only indirectly impacted LHDs, which could explain the insignificant findings

from the analysis. As the literature shows, the HITECH Act was instrumental in spurring the adoption of health IT through mandates and incentives to physicians and hospitals (Adler-Milstein et al., 2014; Gold & McLaughlin, 2016). Consequently, since the HITECH Act did not appropriate funding to assist public health agencies in the implementation of EHRs and HIEs, LHDs' limited resources prevented the adoption of health IT. Nevertheless, the MU 2 regulation that requires eligible professionals to electronically transmit immunization records, laboratory results, and syndromic surveillance could incentivize the federal and state governments to dedicate more resources to assist LHDs with the adoption of health IT, especially if the goal is to create a nationwide, interoperable and secure electronic health information infrastructure.

Mimetic Isomorphic Mechanism

Mimetic isomorphic mechanism as measured by the completion of a CHA was not found to be a statistically significant predictor in the adoption of EHRs or HIEs by LHDs. The results found that the odds of implementing EHRs by LHDs is .26 times less for LHDs that have completed a CHA between three to five years compared to LHDs that have never completed a CHA. Although the result of the mimetic analysis was not statistically significant, it should not diminish the value of participating in a CHA. CHA creates a formal partnership through collaboration within the local public health system to engage in activities to promote healthy communities, which is especially critical to control communicable/infectious diseases. Collaboration encompasses the many forms of engagement including networking, coordinating and cooperation. Networking although informal allows ideas to be shared, coordinating involves sharing of ideas and also altering activities for a formal purpose and

cooperation takes it one step further by sharing resources as well (NACCHO, 2014). Mimetic isomorphic mechanism describes the uncertainty that faces organizations, which in turns drives their behavior to mimic their counterparts. By conducting CHAs, it is an important step towards identifying the needs and issues of the community. Findings from a CHA may indicate other needs that are more of a priority compared to the implementation of EHRs and HIEs. (National Association of County and City Health Officials, 2016). Nonetheless, the implementation of EHRs and HIEs have the potential to streamline workflow and improve efficiency, which may be prudent for LHDs to consider implementing.

Interestingly, governance structure and revenue as the control variables were found to be statistically significant along with the completion of a CHA in the implementation of EHRs. Contrarily, in a previous study conducted in 2015 (McCullough et al., 2015), the findings found that state governance control was negatively associated with EHR use, while revenue was positively associated with the implementation of EHR. The findings from this study suggest that the completion of a CHA alone cannot drive organizational change. As demonstrated by the results of the analysis, governance and revenue are critical components in driving the adoption of EHRs by LHDs. This may also explain why the completion of a CHA was not statistically significant in the adoption of HIEs because governance structure was not found to be significant. Without the support of either the local or state government, barriers will exist in the adoption of HIEs.

Normative Isomorphic Mechanism

Normative isomorphic mechanism as measured by the employment of IS specialists was found to be a statistically significant predictor of the implementation of both EHRs and HIEs. Normative isomorphic mechanism describes professionalization within an organization. The findings from this study suggest that the employment of information system specialists drives the implementation of both EHRs and HIEs by LHDs. Interestingly, in a 2005 informatics report on LHDs, the report indicated that staff training on health IT included locating evidence-based and consumer health information on the Internet; basic computer applications, using and interpreting qualitative and quantitative data; using software analytical tools; designing and maintaining a public health Web site; and confidentiality (NACCHO, 2007). Because IT systems were not as sophisticated compared to the IT systems today, the employment of IS specialists was most likely not a necessity. However, because of the push to adopt EHRs and HIEs by LHDs and the ability for these systems to be interoperable, the employment of IS specialists is critical in supporting and maintaining these systems. Cross-training LHD staff member is no longer sufficient to meet the needs of the systems implemented by LHDs. The results indicate the LHDs are making a long-term commitment in the adoption of health IT by employing IS specialists, rather than focusing on training current LHD staff members.

In summary, based on the findings of the study, normative force was most impactful in driving the adoption of both EHRs and HIEs by LHDs. Mimetic force was significant in driving the adoption of EHRs but not HIEs. Lastly, coercive force was not statistically significant in driving the adoption of either EHRs or HIEs. Previous studies from an institutionalist perspective have found that coercive forces (Zhang & Wan, 2007) were more influential in

driving change, while other studies have found that all three forces are equally influential (Teo et al., 2003). Of importance to note is that coercive forces including regulative systems have been blamed for engendering evasion rather than compliance. Rather, normative and cognitive processes have a greater effect on organizational acceptance of change (Dacin, Goodstein, & Scott, 2002). Similarly, Greenwood, Suddaby, and Hinings (2002) examined the political pressures on accounting organizations, specifically the important role professional associations contribute in shaping change. Their findings suggest that professional organizations legitimized the value of incorporating management advisory services, which led to the extension in the scope of services offered by accounting firms. Health IT associations such as HIMSS and the American Health Information Management Association (AHIMA) is also influential in engendering change. These associations offer continuing education credits, certifications, educational resources and hold numerous conferences throughout the year. Thus, these associations greatly impact the knowledgebase and skills of information specialists, in which they bring back to their LHDs.

Overall Health Outcomes

This is one of the few studies that analyzed the impact of the adoption of EHRs and HIEs on population health at the county level. The results from the study show that the adoption of EHRs does lead to the overall improvement of population health, while the adoption of HIEs was not found to be statistically significant at improving population health. The study results validate the empirical studies that find that the adoption of EHRs leads to overall improved health.

Although the benefits and values derived from the implementation and use of EHRs are mixed, empirical research on the effects of EHRs has shown that the adoption of EHRs does lead to improved overall health, a reduction in medical errors, improved clinical decision support, and improved patient satisfaction (Abramson et al., 2014; Kirsten et al., 2009; McCullough et al., 2010). Further, because of the HITECH Act, the adoption of EHRs has grown exponentially in the last decade or so (Adler-Milstein et al., 2014). As hospitals and physicians see the value in the adoption of EHRs, LHDs also see the value in the adoption of EHRs. The results from this study signify that the adoption of EHRs by LHDs does lead to improved overall health outcomes from a county-level perspective.

With regard to the adoption of HIEs by LHDs, the findings did not support the hypothesis that the adoption of HIEs by LHDs led to improved overall health outcomes at the county level. Evidence from the literature could provide explanations as to why the study came across this finding. First, the adoption of HIEs is not as widespread when compared to the adoption of EHRs (Shah, Vest, Lovelace, & McCullough, 2016). Barriers, including small jurisdiction and local governance structure, all limit the ability of LHDs to participate in HIEs. Second, HIE requires multiple organizations to implement HIEs that are interoperable and can transfer medical information electronically. Thus, the reliance on other organizations, specifically LHDs, to implement HIEs that are also interoperable poses significant challenges.

This is one of the few studies to study the impact of the adoption of EHRs and HIEs on population health at the county level, and the findings align closely with the current literature on the adoption of EHRs and HIEs by hospitals and physician offices. Future research will need to

focus more on the impact of health IT adoption on population health with longitudinal panel data.

Implications

Institutional theory has been used to understand organizational change and the driving forces behind that change since DiMaggio and Powell (1983) and Meyer and Rowan (1977) first brought the theory to light. Since then, institutional theory has been used in healthcare studies to provide guidance in improving healthcare quality in nursing homes and in the adoption of human immunodeficiency virus (HIV) prevention practices amongst the nation's outpatient substance-abuse treatment units (D'Aunno et al., 1999; Zhang & Wan, 2007). To understand the driving forces behind the adoption of health IT by LHDs, institutional theory has guided this research study to understand what mechanisms promote the adoption of health IT by LHDs.

The results from the study prove that in order for legislation to be impactful, it needs to directly impact the stakeholders of interest. The HITECH Act proved successful in spurring the adoption of EHRs by hospitals and physicians; however, because LHDs were not its intended audience, the adoption of EHRs and HIEs has lagged behind hospitals and physician offices. This situation would lead us to believe that legislation needs to provide resources, financial support, and incentives to spur the adoption of EHRs and HIEs by LHDs. The findings from this study in which EHR adoption led to the improvement of overall health outcomes also provides evidence to support the adoption of EHRs by LHDs. As evident from the literature on EHR adoption and its impact on health outcomes, the results align with empirical studies that find EHRs lead to improved health outcomes in hospital settings and physician offices. The

study validates the positive impact of the adoption of EHRs on health outcomes, specifically from a population health perspective, which few empirical studies thus far have sought to analyze. The implications of this study could mean that more policies need to focus on supporting the adoption of health IT by LHDs. Moreover, with legislation promoting and incentivizing the adoption of health IT, HIEs have the potential to positively affect population health at the county level, even though HIEs were not found to be statistically significant in this study.

Regarding community health assessments, CHAs were not found to be effective in the adoption of EHRs or HIEs. CHAs provide a snapshot of the needs of the local community for LHDs. They allow for planning to take place to tackle the most pressing issues of concerns. As a form of mimetic isomorphic mechanism, CHAs provide LHDs faced with uncertainty a direction to follow. In this case, CHAs assesses the health of the local community, its needs, and areas of concerns. While CHAs were not found to drive the implementation of EHRs and HIEs, it does open the dialogue of harness the power of technology. LHDs can harness technology to streamline their workflow, improve patient services and electronically transmit data to enhance surveillance and better control communicable diseases.

Further, engagement of community leaders and creating community partnerships is critical to drive organizational change. LHDs can consider performing CHAs on a more frequent basis to ensure they are perpetually focused on the needs of their community while having a clear idea of what other nearby LHDs are implementing to improve their community's health. Thus, if LHDs that serve similar demographics and have similar organizational structure are uncertain about the adoption of health IT, the engagement of community leaders can steer LHDs in similar paths in an effort to improve their overall population health outcomes.

The employment of IS specialists, a form of normative isomorphic mechanism, was the only mechanism found to be a statistically significant predictor in the adoption of both EHRs and HIEs. LHDs that employ IS specialists are more likely to adopt EHRs and HIEs. The findings describe the association between health IT adoption and the employment of IS specialists. This study however does not determine whether the adoption of EHRs and HIEs came before the employment of IT specialists and vice versa. What this study does tell us is that LHDs are making a long-term commitment in adopting fully-integrated EHRs and HIE systems because they are employing IS specialists rather than cross training LHD staff member who may not come from an IT background or use consultants who would only be there from implementation to the go-live date. By employing IT specialists, LHDs understands the importance of the role that health IT plays in our healthcare environment today. Thus, LHDs need to consider their workforce and the population that it serves and evaluate the need for IS specialists on the team, especially since the study found that the adoption of EHRs does lead to improve population health.

The value derived from the implementation of EHRs and HIEs by LHDs deserves attention because of its abilities to enhance the services provided at LHDs. Health departments provide many types of healthcare services, thus just as health IT is critical in hospitals and doctor's office, it is also important for LHDs to use health IT to electronically capture patient information. Medical information that is electronically captured can also be transferred to other LHDs. EHRs and HIEs can help to reduce duplicative tests and track patients who may use both emergency departments and LHDs for services. Thus, it can help to reduce the misuse of the emergency department when the LHDs offers primary care services to the community.

Finally, although some results were not statistically significant, because institutional theory posits the uniformity of organizational behavior, it does not mean that differences were not observed, it just indicates uniformity amongst LHDs which is what institutional theory examines.

Limitations

This section addresses the limitations inherent in this study. Given that this study spans the years from 2008 to 2013, other legislations, particularly the Affordable Care Act (ACA) which was implemented on March 23, 2013, may have had an impact on the adoption of health IT. The ACA had provisions to improve the quality of care through the effective use of health IT (Health Resources & Services Administration, 2012). Nevertheless, the provisions within the HITECH Act focus entirely on the adoption of health IT. Health IT within the ACA legislation is only a minor part of the legislation. As a result, the HITECH Act will have more of an influence on the implementation of health IT than the ACA.

Next, the use of secondary data presents its own set of limitations, as the study can only analyze the data that are available in the data source. First, the Profile studies provided definitions for many items on its questionnaire; however, not all items or terms were defined. Consequently, respondents may have interpreted questions, items, and terms differently. Missing data was also another limitation in the Profile studies. The questions on finance was one example in which the question showed large amounts of missing data. Third, there are slight differences between the 2008 and 2013 questionnaire: a) The 2008 version did not contain a population-size-served variable; b) the governance structure variable in the 2008 Profile Study

only had two categories, state and local, while the 2013 Profile Study had three categories, state, local, and both; and c) in measuring the level of EHR and HIE activity, the 2008 Profile Study offered five categories (not aware, aware, investigating or have investigated, planning to implement, and have implemented) to select from, while the 2013 Profile Study only offered four categories (no activity, have investigated, planning to implement, and have implemented).

Finally, to analyze the hypotheses in the study, datasets had to be merged. As a result, many observations were lost. Because of this, the counties of Connecticut and Vermont were omitted from the analysis and have no counties represented in this study. Further, counties from the states of Hawaii and Rhode Island are not represented in this study because the public health system in these two states are operated by the state health department and were not included in the Profile Studies (NACCHO, 2009). These omissions could negatively impact the generalizability of the study. Nevertheless, the sample sizes were still sufficient for each of the statistical analyses, and counties from 47 states were represented in the study.

Directions for Future Research

Future research should include other measures of the three isomorphic mechanisms of institutional theory, for example using accreditation as a measure of normative isomorphic mechanism. Accreditation is one attempt to standardize the performance of LHDs. Currently, the Public Health Accreditation Board (PHAB) leads a voluntary public health accreditation initiative across the nation (Riley, Bender, & Lownik, 2012).

Additionally, as noted, health IT comes in many forms, and LHDs adopt not only EHRs and HIEs but also other health IT of importance to LHDs, including immunization registries,

electronic disease reporting systems, and syndromic surveillance. These types of health IT also can impact population health and would be worthwhile to evaluate in future studies.

Further, future research should include an in-depth analysis on the values derived from the implementation of health IT, specifically EHRs and HIEs. There is much empirical research examining the values derived from the implementation of HIT at the hospital and physician-office level, however, little is known about the values derived from the implementation of EHRs and HIEs by LHDs. As mentioned previously, the HIMSS IT Value Suite offers a path in identifying values derived from health IT. However, the Electronic Medical Record Adoption Model (EMRAM) score, which scores hospitals on their electronic medical records capabilities should also be explored in future research pertaining to LHDs (HIMSS Analytics, 2017). LHD's health IT capabilities can be compared to their local hospital's IT capabilities based on the EMRAM score. Thus, disparities in health IT adoption by LHDs can be identified and hopefully, be the impetus to promote the adoption of health IT by LHDs.

Accountable care organizations (ACOs) as created under the ACA, is a model of care that focuses on a specific population group (i.e. Medicare) in which health care providers and hospitals agree to provide coordinate care. Because the ACO model, a value-based payment model focuses on population health and the continuity of care, health IT plays a significant role in the continuum of care when patients move from one provider to the next. For ACOs to be successful, the capabilities of their health IT need to include care coordination, assessment and risk stratification, cohort management, engagement of patients and caregivers and for reporting purposes Thus, future research needs to examine the impact of ACO's health IT adoption and its impact on population health (Robinson, Coughlin & Palmer, 2014; Centers for Medicare & Medicaid Services, 2017).

Because the secondary data sources used in this study are from the NACCHO and the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute, data were collected on a three-year basis or annually in the case of the County Health Rankings dataset. Future research should include qualitative and longitudinal studies to analyze the impact of the adoption of health IT on population health. Qualitative study is particularly salient for further analysis on community health assessments and how effective it is for driving community changes as LHDs partner with the local community.

Finally, from a theoretical perspective, the incorporation of the diffusion of innovation theory espoused by Rogers (1962) with institutional theory allows for a more in-depth understanding of why and when LHDs choose to adopt health IT.

Conclusion

This study examined the driving forces of the adoption of health IT as guided by institutional theory and examined the impact health IT has on population health. Findings showed that of the three isomorphic mechanisms (coercive, mimetic and normative), coercion as measured by the implementation of the HITECH Act was not a driver in the adoption of health IT (EHR and HIE). What this indicates is that the coercive force measured at the federal level suggests the uniformity of the HITECH Act as implemented shows no variation at the county level. Perhaps, future research need to focus on the implementation of regulatory forces to demonstrate the variability in health IT adoption outcomes across counties. The findings also demonstrate that mimetic forces as measured by the completion of a CHA was not a significant driver in the adoption of EHR and HIE, while normative isomorphic mechanisms drove the

adoption of both EHRs and HIEs. Finally, the results from the study demonstrate that the implementation of EHRs improved population health at the county level. This study is unique in that it is one of the few studies that is guided by a theoretical approach in analyzing the forces that drive the adoption of health IT by LHDs and in analyzing how health IT impacts population health at the county level. Future studies should focus on analyzing other types of health IT and how those systems impact population health. Lastly, future studies need to identify barriers in health IT adoption by LHDs, and consequently, can drive public policy to promote the adoption of health IT by LHDs.

APPENDIX A: RELEVANT SURVEY QUESTIONS FROM THE 2008 PROFILE STUDY

Indicate your LHD's level of awareness or activity for each of the following information technology areas. (For each row, select only one.)

	Not aware	Aware	Investigating or have investigated	Planning to implement	Have implemented
Electronic health records **(q226)**	**1**	**2**	**3**	**4**	**5**
(Regional) Health Information Exchanges (HIEs or RHIOs) **(q227)**	**1**	**2**	**3**	**4**	**5**

q16: For your most recently completed year, what were the LHD's total *revenues*?
Amount (Enter whole number):

____

Govcat – LHD governance classification
1=unit of state health agency
2=unit of local government

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APPENDIX B: RELEVANT SURVEY QUESTIONS FROM THE 2013 PROFILE STUDY

c0popcat7 **7-level population categories**
1= <25,000
2=25,000 –49,999
3=50,000–99,999
4=100,000–249,999
5=250,000–499,999
6=500,000–999,999
7=1,000,000+

c0govcat **2010 LHD governance classification**
1=unit of state government
2=unit of local government
3=unit governed by both state and local authorities

7. What were the LHD's total *expenditures* and total *revenues* for the most recently completed fiscal year? (Please enter whole number)

	Total expenditures	**Total revenues**
Most recently completed fiscal year	**(c3q15)**	**(c3q16)**

32. Occupations Employed

- **Indicate which of the following categories of public health workers are currently employed by your LHD.**
- **Indicate the FTE of staff in each classification if data are available.**
- **If you cannot determine the FTE of staff in a category, check the "Data on FTEs not available" box.**
- Categorize staff according to their primary job responsibilities or function, not by their degree or education. For example, if a registered nurse is serving as a "public health manager/director", please count this individual as a "public health manager/director" in the chart.
- Note that this is not intended to be an exhaustive list of occupational categories.
- If your LHD has access to staff in certain occupations working a district or regional health department office, check the box for each such occupation.
- Please indicate FTEs for **all** regular full-time, part-time and contractual employees.
- To calculate FTEs, count a full-time employee as 1 FTE, a half-time employee as a 0.5 FTE, etc.

Occupation (Definitions for each occupation provided on the next page.)	Does your LHD currently employ staff in this classification?		Number of FTEs currently Employed	Data on FTEs not available	Staff with this occupation available via district/ region office
	Yes [1]	**No [0]**			
Information systems specialist	**c5q50a**		**c5q50b**	**c5q50c**	**c5q50d**

(Variable values: unchecked= 0, checked= 1)

49. Has a community health assessment been completed for your LHD's jurisdiction? (Select only one) **(c7q147)**

- ☐ **[1]** Yes, within the last three years
- ☐ **[2]** Yes, more than three but less than five years ago
- ☐ **[3]** Yes, five or more years ago
- ☐ **[4]** No, but plan to in the next year
- ☐ **[5]** No

72. Indicate your LHD's level of activity for each of the following information technology areas. (For each row, select only one**)**

IT Area	No activity	Have investigated	Planning to implement	Have implemented
Electronic Health Records **(m4q301)**	**[0]**	**[1]**	**[2]**	**[3]**
Health Information Exchange **(m4q302)**	**[0]**	**[1]**	**[2]**	**[3]**

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APPENDIX C: UNIVERSITY OF CENTRAL FLORIDA IRB APPROVAL LETTER

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901, 407-882-2012 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

NOT HUMAN RESEARCH DETERMINATION

From : **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To : **Tina Yeung**

Date : **January 31, 2017**

Dear Researcher:

On 01/31/2017 the IRB determined that the following proposed activity is not human research as defined by DHHS regulations at 45 CFR 46 or FDA regulations at 21 CFR 50/56:

Type of Review:	Not Human Research Determination
Project Title:	Local Health Departments Adoption of Health Information Technology and the Impact on Population Health
Investigator:	Tina Yeung
IRB ID:	SBE-17-12890
Funding Agency:	
Grant Title:	
Research ID:	N/A

University of Central Florida IRB review and approval is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are to be made and there are questions about whether these activities are research involving human subjects, please contact the IRB office to discuss the proposed changes.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Signature applied by Gillian Amy Mary Morien on 01/31/2017 01:58:08 PM EST

IRB Coordinator

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