The Effects of Electronic Health Records and Teaching Status on Mortality, Cost, and Length of Stay in New York State Hospitals

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Approval Page

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Abstract

Becoming more efficient in healthcare delivery has been a recurring theme in the U.S. for decades. Several laws have been enacted by Congress over recent decades aimed at incentivizing U.S. healthcare delivery to become more efficient and cost effective. Recently, electronic health records have been touted as a technology-centric path toward healthcare efficiency, with the Federal government incentivizing large-scale adoption of these systems. The evidence to prove that electronic health records lower cost and increase clinical quality is conflicting and nuanced. Additionally, teaching hospitals have historically been outliers for both the quality and the cost of their healthcare services for various reasons. A possible interaction effect between hospital teaching status and electronic health records has not been previously investigated. The purpose of this quantitative correlational study was to examine the performance differences between teaching and non-teaching hospitals in the post-electronic health record implementation landscape, specifically looking at possible interaction effects between electronic health records and hospital teaching status. This research study confirmed previous research that major teaching hospitals cost more and their patients stay in the hospital longer than non-teaching or minor teaching hospitals. Pneumonia risk adjusted mortality was slightly higher at major teaching hospitals. The most salient finding of this study was that electronic health records seem to have no effect on quality, cost, or efficiency in New York State hospitals. This seems to support the notion that electronic health record use and effects may be nuanced and complex. There was also no detected interaction effect between electronic health record status and the teaching status of New York State hospitals.

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Chapter 1: Introduction

The differences between teaching and non-teaching hospitals have been studied in previous decades with a keen focus on the cost of care and the efficiency of these two different types of provider organizations (Hartley, Markowitz, & Komaroff, 1989; MacKenzie, Willan, Cox, & Green, 1991; Rosko, 2004; Williams, Matthews, & Hassan, 2007). In these previous studies, teaching hospitals were generally found to be more expensive (between 10% to 30%), and less efficient than their non-teaching counterparts (MacKenzie et al., 1991; Williams et al., 2007). Since these studies were completed, a wave of information technology adoption has swept through healthcare in the United States with the passing of two influential laws—the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, and the Patient Protection and Affordable Care Act (PPACA) of 2010 (Fontenot, 2013; Galbraith, 2013).

The HITECH Act provided $27 billion dollars in incentives to bring about a greater use of technology in healthcare, and specifically the increased use of electronic health records, or EHRs (Galbraith, 2013). The United States stands out among developed nations for the amount of money spent on healthcare services for its citizens (Huerta, Thompson, Ford, & Ford, 2013). For example, the U.S. spends roughly 17% of its GDP on health services (Huerta et al., 2013). EHRs have been touted as a potential cost-saving measure along with the potential to increase organizational efficiency, and there is some research to support this viewpoint (Harrison & Daly, 2009; Lee & Choi, 2016; Zlabek, Wickus, & Mathiason, 2011).

Studies performed after the passing of these two instrumental pieces of legislation that examined the differences between teaching hospitals and non-teaching hospitals have largely focused on specific patient conditions or sub-populations and have not looked at teaching hospitals in the light of organization-level attributes or performance post-EHR implementation (Chin, Wilson, Bang, & Romano, 2014; Dolmatova et al., 2016; Hyder, Sachs, Ejaz, Spolverato, & Pawlik, 2013; Sandhu et al., 2013). Teaching hospitals traditionally have been outliers when it came to the costs associated with healthcare service delivery (Dolmatova et al., 2016; Fineberg, Oglesby, Patel, Pelton, & Singh, 2013; Zafar et al., 2015). In the U.S., the educational mission of teaching hospitals is often funded via Medicare through Graduate Medical Education (GME) codes to help cover the additional costs of training resident physicians (Chandra, Khullar, & Wilensky, 2014). With the large-scale implementation of EHRs in all types of hospitals in recent years, the organization-level performance and quality differences between teaching and non-teaching hospitals should be re-examined with an eye toward any potential interaction between these EHRs and teaching status.

Statement of the Problem

Recent U.S. healthcare legislation reform has created large incentives for clinical information system adoption, specifically electronic health records (Lee & Choi, 2016). The HITECH Act provided healthcare organizations with tens of billions of dollars in incentives over the course of a decade to implement and use EHRs meaningfully (Lee & Choi, 2016). Though the U.S. healthcare enterprise is rapidly implementing EHRs and other clinical information systems due to large governmental incentives, the evidence to prove that these systems lower cost and increase clinical quality is conflicting and nuanced (Burke, Becher, Hoang, & Gimbel, 2016; Sharma, Chandrasekaran, Boyer, &

McDermott, 2016; Tall, Hurd, & Gifford, 2015; Yanamadala, Morrison, Curtin, McDonald, & Hernandez-Boussard, 2016).

The teaching status of hospitals and its effect on hospital cost and efficiency has been studied over the last several decades (Rosko, 2004; Williams et al., 2007) but there are few recent studies looking at these factors based on data after the recent healthcare reform legislation and corresponding EHR implementations at an organizational level (Chin et al., 2014; Dolmatova et al., 2016; Zafar et al., 2015). The importance of studying the effects of EHRs on organizations in the post-healthcare reform landscape has been identified as an area of needed research (Gholami, Añón Higón, & Emrouznejad, 2015).

The problem is that the effects of EHR implementations on hospitals have been varied and nuanced and that teaching hospitals have traditionally differed from other hospitals when it comes to their service delivery. Research should be conducted to look at how EHRs may have affected teaching hospitals in ways different than non-teaching hospitals. By examining this potential distinction, healthcare professionals and lawmakers may be able to refine their application of this technology in these organizations, and properly incentivize its use for the benefit of the patient, the hospital, and the nation.

Purpose of the Study

The purpose of this quantitative correlational study is to examine the performance differences between teaching and non-teaching hospitals in the post-EHR implementation landscape, specifically looking at possible interaction effects between EHRs and hospital teaching status. This study will also include analyses that may help to confirm or disconfirm past research findings regarding the cost differences between teaching and non-teaching hospitals as well as potential quality and efficiency differences after the implementation of EHRs. This knowledge may help to establish whether EHRs have made a meaningful impact on the cost and efficiency of care (in addition to the quality of care) in teaching hospitals. There will also be an attempt to re-establish the baseline cost differences between teaching and non-teaching hospitals post-EHR, where teaching hospitals are further stratified into minor and major teaching hospitals per guidance from previous research (Navathe, Silber, Zhu, & Volpp, 2013).

The current analysis around EHRs, particularly with respect to their application within teaching hospitals, still has several unexplored frontiers. The United States is firmly on its journey of EHR adoption. Some research remains relatively ambiguous and conflicting when it comes to the larger picture of how EHRs affect hospitals (Burke et al., 2016; Sharma et al., 2016; van Poelgeest, Heida, Pettit, de Leeuw, & Schrijvers, 2015). Teaching hospitals, and the potential effects of EHR implementations on those organizations, have largely not been studied at organizational levels in the post-healthcare reform landscape. This study also adds insight in this area of research.

Theoretical Framework

The research outlined in this study is focused to address the questions of quality, efficiency, and costs associated with teaching hospitals as they have transitioned through the HITECH Act and PPACA era, post-EHR implementation. One of the potential research gaps in the existing literature appears to be that teaching hospitals are largely not studied using organization-level variables after their EHR implementation and the bulk of studies are focused on sub-populations of patients as opposed to focused on organizational performance, or includes data that is largely pre-EHR implementation (Bir et al., 2015; Chin et al., 2014; Sheetz, Dimick, & Ghaferi, 2016).

There are two key theories that form the foundation of this research. The theories explored in this section are largely divided by the two dimensions of the problem statement. The first dimension relates to the use of EHRs within organizations and how those information systems may contribute to an organization's efficiency and quality. The second dimension relates to how teaching hospitals have historically compared to non-teaching hospitals, by measures such as quality of care, cost, and efficiency. The intersection of these two areas is the focus of this research—have EHRs affected teaching hospitals in ways potentially different than non-teaching hospitals?

Within the literature surrounding EHR implementations, most research articles do not explicitly link to a particular theory, either within the information systems research domain or other domains, but some do (Sharma et al., 2016). For example, Sharma et al. (2016) linked to Organizational Information Processing Theory (Galbraith, 1974), and note that these types of information systems can integrate various departments within an organization for the benefit of patient care. Other researchers also link to various quality improvement theories, namely those proposed by Deming and Crosby (Gholami et al., 2015). These quality improvement theories are primarily focused on quality and efficiency of organizations and do not explicitly link to the implementation of information systems, such as EHRs.

Within the literature surrounding the analysis of teaching versus non-teaching hospitals, in similar fashion, most researchers do not explicitly link to a particular foundational theory when comparing these hospitals, but there are some links to theory

(Rosko, 2004). For example, Rosko (2004) linked to Institutional Theory (Scott, 1987) when describing how hospitals determine what amount of uncompensated care to carry. This is relevant as teaching hospitals take on more uncompensated care than non-teaching hospitals which could affect their overall cost standing (Rosko, 2004).

Nature of the Study

The data for this quantitative correlational study came from several different sources. All data is currently publicly available and came from the Centers for Medicare and Medicaid Services (CMS) and the New York State (NYS) Data Portal. The following five individual files were used: (1) NYS All Payer Hospital Inpatient Discharges data for the year 2014, (2) CMS Hospital Quarterly Measures file from the Hospital Compare data for the year 2014, (3) CMS Impact file data for the year 2014, (4) NYS Health Facility General Information data, and (5) NYS All Payer Inpatient Quality Indicators data for 2014.

The actual analysis for this research encompassed three two-way multivariate Analysis of Variance (MANOVA) hypothesis tests. The two independent variables for this MANOVA test are EHR category (whether an EHR is present or not in each hospital), and the teaching category of the hospital (non-teaching, minor teaching, or major teaching hospital), based on previous research (Navathe et al., 2013). There has been a previously identified difference in mortality between minor teaching hospitals and non-teaching hospitals that is worth exploring in this study (Navathe et al., 2013). The dependent variables include: acute myocardial infarction (AMI) mortality risk adjusted rate, heart failure mortality risk adjusted rate, pneumonia mortality risk adjusted rate, AMI total costs, heart failure total costs, pneumonia total costs, AMI length of stay, heart failure length of stay, and pneumonia length of stay consistent with analysis methods from previous research (Carretta, Chukmaitov, Tang, & Shin, 2013; Chin et al., 2014; Dolmatova et al., 2016).

A two-way multivariate ANOVA (MANOVA) design is the most appropriate to answer this type of question as the hospitals being evaluated are grouped in different ways. This grouping scheme (EHR or no EHR; non-teaching, minor teaching, or major teaching hospital) allows the inter-group differences to be evaluated statistically. These independent variables combined with several dependent variables allow the researcher to answer not only if the hospital groups have statistically significant differences between them but, by running post-hoc analyses, point to which combination of variables are significant along with their corresponding effect sizes.

Research Questions

These research questions will add to the body of knowledge in the post-EHR domain and potentially may help to clarify existing conflicting findings of past research by investigating several different dimensions of hospital performance with respect to EHR adoption and hospital teaching status.

RQ1. How much of an effect do EHRs have on hospital mortality rate as measured by AMI mortality risk adjusted rate?

RQ2. How much of an effect do EHRs have on hospital mortality rate as measured by heart failure mortality risk adjusted rate?

RQ3. How much of an effect do EHRs have on hospital mortality rate as measured by pneumonia mortality risk adjusted rate?

RQ4. How much of an effect do EHRs have on hospital efficiency as measured by AMI length of stay?

RQ5. How much of an effect do EHRs have on hospital efficiency as measured by heart failure length of stay?

RQ6. How much of an effect do EHRs have on hospital efficiency as measured by pneumonia length of stay?

RQ7. How much of an effect do EHRs have on hospital cost performance as measured by AMI total costs?

RQ8. How much of an effect do EHRs have on hospital cost performance as measured by heart failure total costs?

RQ9. How much of an effect do EHRs have on hospital cost performance as measured by pneumonia total costs?

RQ10. How much of an effect does teaching status have on hospital mortality rate as measured by AMI mortality risk adjusted rate?

RQ11. How much of an effect does teaching status have on hospital mortality rate as measured by heart failure mortality risk adjusted rate?

RQ12. How much of an effect does teaching status have on hospital mortality rate as measured by pneumonia mortality risk adjusted rate?

RQ13. How much of an effect does teaching status have on hospital efficiency as measured by AMI length of stay?

RQ14. How much of an effect does teaching status have on hospital efficiency as measured by heart failure length of stay?

RQ15. How much of an effect does teaching status have on hospital efficiency as measured by pneumonia length of stay?

RQ16. How much of an effect does teaching status have on hospital cost performance as measured by AMI total costs?

RQ17. How much of an effect does teaching status have on hospital cost performance as measured by heart failure total costs?

RQ18. How much of an effect does teaching status have on hospital cost performance as measured by pneumonia total costs?

RQ19. How do major, minor, and non-teaching hospitals' mortality rate compare with and without an EHR as measured by AMI mortality risk adjusted rate?

RQ20. How do major, minor, and non-teaching hospitals' mortality rate compare with and without an EHR as measured by heart failure mortality risk adjusted rate?

RQ21. How do major, minor, and non-teaching hospitals' mortality rate compare with and without an EHR as measured by pneumonia mortality risk adjusted rate?

RQ22. How do major, minor, and non-teaching hospitals' efficiency compare with and without an EHR as measured by AMI length of stay?

RQ23. How do major, minor, and non-teaching hospitals' efficiency compare with and without an EHR as measured by heart failure length of stay?

RQ24. How do major, minor, and non-teaching hospitals' efficiency compare with and without an EHR as measured by pneumonia length of stay?

RQ25. How do major, minor, and non-teaching hospitals' cost performance compare with and without an EHR as measured by AMI total costs?

RQ26. How do major, minor, and non-teaching hospitals' cost performance compare with and without an EHR as measured by heart failure total costs?

RQ27. How do major, minor, and non-teaching hospitals' cost performance compare with and without an EHR as measured by pneumonia total costs?

Hypotheses

The hypotheses for this research are listed below. These specific hypotheses are directly related to each of the research questions in the previous section.

$H1_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by AMI mortality risk adjusted rate.

$H1_a$. EHRs have a statistically significant effect on hospital mortality as measured by AMI mortality risk adjusted rate.

$H2_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by heart failure mortality risk adjusted rate.

$H2_a$. EHRs have a statistically significant effect on hospital mortality as measured by heart failure mortality risk adjusted rate.

$H3_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by pneumonia mortality risk adjusted rate.

$H3_a$. EHRs have a statistically significant effect on hospital mortality as measured by pneumonia mortality risk adjusted rate.

$H4_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

$H4_a$. EHRs have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

$H5_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

$H5_a$. EHRs have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

$H6_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

$H6_a$. EHRs have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

$H7_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by AMI total costs.

$H7_a$. EHRs have a statistically significant effect on hospital cost performance as measured by AMI total costs.

$H8_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H8_a$. EHRs have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H9_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

$H9_a$. EHRs have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

$H10_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by AMI mortality risk adjusted rate.

$H10_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by AMI mortality risk adjusted rate.

$H11_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by heart failure mortality risk adjusted rate.

$H11_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by heart failure mortality risk adjusted rate.

$H12_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by pneumonia mortality risk adjusted rate.

$H12_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by pneumonia mortality risk adjusted rate.

$H13_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

$H13_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

$H14_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

$H14_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

$H15_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

$H15_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

$H16_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by AMI total costs.

$H16_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by AMI total costs.

$H17_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H17_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H18_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

$H18_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

$H19_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by AMI mortality risk adjusted rate.

$H19_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by AMI mortality risk adjusted rate.

$H20_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by heart failure mortality risk adjusted rate.

$H20_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by heart failure mortality risk adjusted rate.

$H21_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by pneumonia mortality risk adjusted rate.

$H21_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by pneumonia mortality risk adjusted rate.

$H22_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by AMI length of stay.

$H22_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by AMI length of stay.

$H23_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by heart failure length of stay.

$H23_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by heart failure length of stay.

H24$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by pneumonia length of stay.

H24$_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by pneumonia length of stay.

H25$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by AMI total costs.

H25$_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by AMI total costs.

H26$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by heart failure total costs.

H26$_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by heart failure total costs.

H27$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by pneumonia total costs.

$H27_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by pneumonia total costs.

Significance of the Study

There are several gaps in research among EHR implementations regarding teaching hospitals post-healthcare reform. There are studies that have shown that teaching hospitals typically have a higher cost of service due to their teaching and research missions, but a large majority of those studies (some of which date back to the 1980's) are using data prior to the HITECH Act (Dolmatova et al., 2016; MacKenzie et al., 1991; Williams et al., 2007). There appears to be a gap in research since the last nationwide legislative push for healthcare reform that compares teaching hospitals to non-teaching hospitals organizationally within the context of EHRs.

In addition to the research gap in existing literature noted above, there are several ambiguities and inconsistencies in extant literature on EHR use and the cost of care and the quality of service delivery. For example, EHR and other HIT systems can have differing effects on healthcare organizations and potentially cancel each other out in some ways (Sharma et al., 2016). Additionally, users of HIT systems and their individual characteristics can affect acceptance of these systems (Ifinedo, 2016). There has also been research that shows no significant impact on workflow efficiency due to EHR implementation (Tall et al., 2015). In fact, some research has shown a reduction in productivity due to EHR implementation (Huerta et al., 2013).

Definition of Key Terms

The following terms are defined more clearly for the reader's understanding.

Electronic health record. Electronic health records (EHRs) are a form of enhanced electronic medical records (EMRs) that include the ability to create and share the complete picture of a patient's care from multiple providers ("Definition and benefits of electronic medical records (EMR)," 2016).

Electronic medical record. Electronic medical records (EMRs) are a more simplistic electronic version of a patient's chart used for care and treatment ("Definition and benefits of electronic medical records (EMR)," 2016).

Minor teaching hospital. A hospital with a resident-to-hospital-bed ratio less than 0.25 but greater than 0 (Navathe et al., 2013).

Major teaching hospital. A hospital with a resident-to-hospital-bed ratio equal to or greater than 0.25 (Navathe et al., 2013).

Non-teaching hospital. A hospital with a resident-to-hospital-bed ratio of 0 (Navathe et al., 2013).

Risk adjustment. Risk adjustment is a modification of reported outcome measures based on statistical procedures to more accurately depict performance and to account for various patient characteristics ("Introduction to measures of quality," 2014).

Summary

After reviewing the general state of literature associated with EHR adoption and use on the three dimensions of analysis (quality of care, cost of care, and efficiency of the healthcare organization), there is a sense of conflicting studies and areas where EHRs have had different effects on hospital performance and quality outcomes (Burke et al., 2016; Sharma et al., 2016; Tall et al., 2015; Yanamadala et al., 2016). There has been research showing positive effects of EHRs on hospital performance (Gholami et al., 2015; Sharma et al., 2016; Yang et al., 2014), negative effects on hospital performance (Brunt & Bowblis, 2014; Huerta et al., 2013; Sharma et al., 2016), and no effects on hospital performance (Burke et al., 2016; Tall et al., 2015; Yanamadala et al., 2016).

Much of this research is prior to the HITECH Act or shortly after (Brunt & Bowblis, 2014; Burke et al., 2016; Sharma et al., 2016). There are few studies that have taken a comprehensive and organizational look at EHR adoption effects with data after the HITECH Act. Similarly, there are several studies that looked at the teaching status of hospitals and its effect on these three analysis dimensions, but there are few studies that have included data years after the HITECH Act and subsequent EHR adoption and use (Bir et al., 2015; Dolmatova et al., 2016; Sheetz et al., 2016). Gholami et al. (2015) have also identified this gap in knowledge and suggested it for a possible future study. This research is designed to help answer this exact question.

Chapter 2: Literature Review

This literature review provides the high-level status of extant knowledge around the effects of Electronic Health Records (EHRs) and the teaching status of hospitals along the dimensions of healthcare service quality, the cost of service delivery, and the efficiency of healthcare organizations. This is particularly relevant considering recent healthcare reform legislation in the United States. In addition to the overview of the available literature in these areas, knowledge gaps are identified and highlighted for potential future research.

The extant literature reviewed that served as the theoretical foundation for this research included published, scholarly, and peer-reviewed articles from many journals and databases. For example, EBSCOhost databases, IEEE Xplore Digital Library, ScienceDirect Journals, SpringerLink Journals, MEDLINE, and Web of Science were all searched to provide the list of exemplar studies that are explored in the following sections. These databases were searched using a combination of terms related to electronic health records. For example, ‘Electronic Health Records’ and ‘Costs’; ‘Electronic Medical Records’ and ‘Costs’; Electronic Health Records’ and ‘Quality’; ‘Electronic Medical Records’ and ‘Quality’; ‘Electronic Health Records’ and ‘Efficiency’; ‘Electronic Medical Records’ and ‘Efficiency’; ‘Teaching Status’ and ‘Cost’; ‘Teaching Status’ and ‘Quality’; ‘Teaching Status’ and ‘Efficiency’; ‘Academic Hospital’ and ‘Cost’; ‘Academic Hospital’ and ‘Quality’; ‘Academic Hospital’ and ‘Efficiency’ with similar permutations of ‘EHR’, ‘EMR’, and ‘AMC’ (academic medical center) were all used to return relevant research on this topic. The dates of the publications reviewed were primarily from 2011 and later but other seminal works or related prior foundational research from before 2011 was also reviewed (Galbraith, 1974; Harrison & Daly, 2009; Hartley, Markowitz, & Komaroff, 1989; MacKenzie, Willan, Cox, & Green, 1991; Rosko, 2004; Scott, 1987; Williams, Matthews, & Hassan, 2007).

Healthcare Reform Legislation

Congress, via healthcare reform legislation, has attempted to change the landscape of American healthcare service delivery for several decades. In several of these iterations new but similar patterns have emerged, but they were often variations on the same theme that included reductions in the payment for services or some type of shared risk model (Jost, 2012). These different models have influenced those within the healthcare industry, both organizations and individuals, to become more efficient and cost effective to help the industry reduce costs at a national level and lessen the burden of healthcare delivery on the nation itself (Jost, 2012).

One of the most innovative changes in recent years has included incentives for healthcare information technology adoption, along with new industry reform changes. For example, the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 included unprecedented incentives for healthcare organizations to implement Electronic Health Records (Lee & Choi, 2016). Healthcare organizations must not only implement EHRs but they must attest to their meaningful use in various stages (Lee & Choi, 2016). Total incentives provided by the Federal government are close to $30 billion (Lee & Choi, 2016). These HITECH Act incentives have fueled a rapid expansion of capital spending on healthcare information technology. For example, it has been estimated that the healthcare industry spent over $34 billion in 2014 on information technology, and that it will spend over $56 billion in 2017 (Sharma, Chandrasekaran, Boyer, & McDermott, 2016).

Electronic Health Records and Clinical Information Systems

Electronic Health Records and other clinical information systems have been widely studied both in this nation and in other nations around the world (Adler-Milstein, Everson, & Lee, 2015; Ben-Assuli, Shabtai, & Leshno, 2013; Brunt & Bowblis, 2014; Henning, Horng, & Sanchez, 2013; Lee & Choi, 2016; Lee, Kuo, & Goodwin, 2013; Sharma et al., 2016). The effects of this technology, as they apply to several dimensions of service delivery, are vital to understanding the current landscape of the healthcare industry. In this literature review, the primary effects of EHR adoption are explored along three main dimensions: (1) the effects on the quality of healthcare service delivery as a result of EHR use, (2) the effects on the cost of care of those healthcare services as a result of EHR use, and (3) the effects on the efficiency of the particular healthcare organization as a result of EHR use. In addition to these three dimensions, an overview of the years of data available in these studies will be helpful to put much of these analyses into context.

The first dimension explored is that of the effects of EHR use on the quality of healthcare services. At an overview level, EHR use has proven to provide mixed results along the dimension of quality of healthcare service delivery. For example, there are examples where EHR use positively affected (lowered) mortality, reduced hospital readmissions, and reduced medical errors (Ben-Assuli, Shabtai, & Leshno, 2013; Gholami, Añón Higón, & Emrouznejad, 2015; Zlabek et al., 2011). On the other hand, there were examples of mixed quality performance due to EHR use, where there was either no significant difference in performance after EHR adoption or there was an increase in quality in one area while there was a decrease in quality in another area (Lee, Kuo, & Goodwin, 2013; Sharma, Chandrasekaran, Boyer, & McDermott, 2016; van Poelgeest, Heida, Pettit, de Leeuw, & Schrijvers, 2015).

The second dimension explored is that of the effects of EHR use on the cost of care of healthcare services. Again, in this area, EHR use has been found to be associated with mixed results at an industry level. For example, one study has found that EHR adoption has lowered the cost of care (Zlabek et al., 2011). One study found mixed results when it comes to the cost of healthcare service delivery (Sharma, Chandrasekaran, Boyer, & McDermott, 2016). One study found that EHR use, specifically advanced EHR use, increased the cost of care by 7% (Teufel, Kazley, Ebeling, & Basco, 2012).

The third dimension explored is that of the effects of EHR use on the efficiency of the healthcare organization that implemented and used the EHR. This dimension of EHR adoption and use is filled with the most examples of mixed results. For example, there are studies that show EHR use increases revenue, reduces length of stay, and increases efficiency (Gholami, Añón Higón, & Emrouznejad, 2015; Lee & Choi, 2016; Lee, Kuo, & Goodwin, 2013; Yang et al., 2014; Zlabek et al., 2011). There are also studies that show EHR adoption and use do not significantly affect organizational performance (Adler-Milstein, Everson, & Lee, 2015; Bae & Encinosa, 2016; Henning, Horng, & Sanchez, 2013; Tall, Hurd, & Gifford, 2015). Finally, there are studies that show that EHR adoption and use have had a negative effect on organizational performance, when it comes to productivity and patient throughput (Huerta, Thompson, Ford, & Ford, 2013; Lam, Lee, & Chen, 2015).

The data associated with these studies varies in dates but is generally after 2000. The oldest study data listed in this section is from 2000 and the latest is inclusive of 2013 and 2014. Most studies outlined in this literature review are from the 2004 to 2010 date range, largely prior to the HITECH Act of 2009.

Theoretical Foundation – Information Systems Theory

When reviewing the existing literature associated with the effects of EHR adoption on healthcare facilities, a large proportion of studies do not mention or include an underlying Information Systems (IS) theory. There are a few exceptions, however, and these studies can help the reader to properly frame and evaluate the effectiveness of these information systems within IS domain of knowledge. The two IS theories that were identified by researchers were Organizational Information Processing Theory (Sharma et al., 2016) and Diffusion of Innovations Theory (Ben-Assuli, Shabtai, & Leshno, 2013). Additionally, outside of the IS domain of theories, various quality improvement theories have also been linked with EHR implementation and use (Gholami, Añón Higón, & Emrouznejad, 2015).

Organizational Information Processing Theory (OITP) was originally developed by Galbraith and essentially proposes a link between task uncertainty and information needed to complete the task (Galbraith, 1974). The fundamental concept is that as task uncertainty increases, the information needed to complete the task also increases (Galbraith, 1974). Sharma et al. (2016) use OITP to describe the way in which healthcare information systems can help to coordinate activities between different units in an organization, thereby reducing uncertainty. Diffusion of Innovations Theory, in the context of Social Contagion Theory, has been discussed by Gan (2015) when considering how physicians may resist or adopt EHRs. Ben-Assuli, Shabtai, and Leshno (2013) suggested in their study that future work should include collection of various physician attributes to better study how these may relate to patterns of EHR and health information exchange use.

Effects of EHRs on Quality

When investigating the effects that clinical information systems and EHRs have on the quality of healthcare services delivered, it is important to realize that the existing literature is largely mixed on the care outcomes that these systems provide. In this section, studies from the last five years will be examined, specifically with a focus on the effects on the quality of healthcare services delivered and the potential benefit to the patients. Eight recent studies will be examined to show effects that clinical information systems and EHRs have on patient care. The studies are arranged chronologically from the newest to the oldest, based on year of publication.

Burke, Becher, Hoang, and Gimbel (2016) studied a longitudinal view of quality on individual patients as a result of EHR use. Specifically, this study examined 537 patients and their corresponding hemoglobin A1C lab values (Burke et al., 2016). This study spanned more than five years and included several different organizations (Burke et al., 2016). The analysis looked at patients six months prior to EHR implementation, six months after EHR implementation, and then again five years after EHR implementation (Burke et al., 2016). The findings indicated that EHR implementation did not have a positive significant relationship on the A1C values of these patients, both six months and five years post-EHR implementation (Burke et al., 2016). This study is significant as it looked longitudinally at a large number of individual patients to see if EHR adoption would potentially improve this important lab value for diabetic patients and found no significant relationships (Burke et al., 2016).

Yanamadala et al. (2016) continued the exploration of EHRs and their impact on patient outcomes as organizations adopt these large information systems. This study was published in 2016, though the data from the analysis is from 2011 and earlier (Yanamadala et al., 2016). This study was observational in nature and utilized the survey data of inpatient healthcare facilities in six different states—Arkansas, California, Florida, Massachusetts, Mississippi, and New York (Yanamadala et al., 2016). Though the latest data is from 2011, the authors looked at differences in patient outcomes from 2008 to 2011 (Yanamadala et al., 2016). The findings of the study indicated that full EHR organizations had lower inpatient mortality rates, though when other hospital factors were considered, there was not a statistically significant relationship between EHR implementation and patient outcomes (Yanamadala et al., 2016).

Sharma et al. (2016) investigated how Health Information Technology (HIT) affects hospital performance. This is an important aspect to study as HIT implementations represent a large capital outlay and a heavy commitment for the healthcare organization (Sharma et al., 2016). This study was a large longitudinal study that encompasses over 3,600 hospitals in the United States from 2007 to 2012 (Sharma et al., 2016). The analysis broke HIT into 76 different categories and combined several different data sources to perform the analysis (Sharma et al., 2016). The analysis also used control variables such as Case Mix Index (CMI) and the teaching status of organizations to help better differentiate organizations (Sharma et al., 2016). The findings in this study were mixed. The post-hoc analysis revealed different effects for organizations depending on whether they implemented EHRs as one of their HIT initiatives (Sharma et al., 2016). EHRs and other HIT together were associated with better clinical outcomes, while EHRs on their own were associated with higher operating costs for the organization (Sharma et al., 2016).

Continuing the analysis of technology's effects in healthcare, Gholami et al. (2015) investigated the potential to improve healthcare quality and efficiency using information systems. The authors also noted a potential balance between investment in these types of information systems and the quality of healthcare services delivered (Gholami et al., 2015). Though the study was published in 2015, the data involved in the analysis is from several data sources from 2004 to 2005 (Gholami et al., 2015). This is certainly prior to the main infusion of incentive money from the HITECH Act of 2009. The sources of this data were from the Thompson Reuters Healthcare data set and the Delta Group (Gholami et al., 2015). These sources included 187 different hospitals during this timeframe (Gholami et al., 2015). The findings indicated a positive relationship with the quality of healthcare services and the use of information systems (Gholami et al., 2015). It was further noted that this positive relationship only extends to mortality, but not necessarily to other areas of healthcare quality (Gholami et al., 2015).

van Poelgeest et al. (2015) investigated the potential link between EHR adoption and patient quality and safety outcomes. The Electronic Medical Record Adoption Model (EMRAM) score that a healthcare organization attains is based on several factors related to their implementation and use of Electronic Medical Records (van Poelgeest et al., 2015). The scale is from one to seven, where stage seven is the highest, most robust use of EMRs throughout an organization (van Poelgeest et al., 2015). The authors investigated the hypothesis that higher stage EMRAM organizations have better patient quality and patient safety outcomes (van Poelgeest et al., 2015). The data from this study came from the HIMSS Analytics EMRAM data set from several Dutch hospitals. The analysis used a combination of the HIMSS Analytics EMRAM data set and other publicly available data from a Dutch healthcare transparency program (van Poelgeest et al., 2015). The findings of the analysis indicated that there was no significant link between the EMRAM score of an organization and its patient quality and patient safety outcomes (van Poelgeest et al., 2015). This study would then add to the body of knowledge that EMR implementation does not make a significant difference in outcomes, at least as measured by EMRAM score.

Brunt and Bowblis (2014) examined the use of information technology in healthcare with a specific focus on primary care physicians. Primary care physicians are often the first doctors that patients see and they treat a wide variety medical conditions as well as coordinate care for other services (Brunt & Bowblis, 2014). The adoption of advanced information systems in smaller practices has been slow even though there are subsidies that these practices could use to implement information technology (Brunt & Bowblis, 2014). The study used data from a 2008 Health Tracking Physician Survey, which was a national survey that includes over 4,700 physicians (Brunt & Bowblis, 2014). The findings of this research indicated that those practices that implement information technology see fewer patients (lower throughput) than those using paper records (Brunt & Bowblis, 2014). There was also no difference in the quality of care delivered due to the use of information technology (Brunt & Bowblis, 2014). This study fits in with extant research and bolsters the idea that information technology can reduce efficiency in certain scenarios without significantly increasing quality.

Additionally, Lee, Kuo, and Goodwin (2013) discussed how the use of an EHR can affect various quality indicators such as mortality, readmission, and length of stay. This study was primarily designed around the effects of EHR on these quality indicators in a 30-day window (Lee, Kuo, & Goodwin, 2013). The researchers found positive support for a reduction in length of stay, but found differing results on the readmission and mortality variables (Lee, Kuo, & Goodwin, 2013). For example, in this study, the researchers noted a reduction in 30-day mortality after EHR implementation, but an increase readmissions within the 30-day window (Lee, Kuo, & Goodwin, 2013). This study supports the concept that EHR implementations have potentially complex effects on organizations and may not offer the simple improvements for all quality indicators.

Ben-Assuli, Shabtai, and Leshno (2013) studied how information technology projects do not always live up to their expectations. Healthcare information technology projects are not necessarily different. The application of information technology in healthcare holds the promise of a more efficient and safer environment (Ben-Assuli, Shabtai, & Leshno, 2013). One way in which a complicated process like healthcare delivery can become more efficient is to reduce waste (Ben-Assuli, Shabtai, & Leshno, 2013). The authors looked at patient hospital readmissions as a form of waste. It is believed that about half of all patient readmissions are avoidable (Ben-Assuli, Shabtai, & Leshno, 2013). This study was conducted in Israel using Health Maintenance Organization data which included approximately 3.8 million patients (Ben-Assuli, Shabtai, & Leshno, 2013). The authors found that a reduced readmission rate due to the review of medical history on an electronic system (Ben-Assuli, Shabtai, & Leshno, 2013).

These eight recent studies show the various mixed results of electronic health records and clinical information systems on patient care. Three of the studies found a benefit to patient care via the reduction of readmissions, lower mortality, and better quality outcomes (Ben-Assuli, Shabtai, & Leshno, 2013; Gholami et al., 2015; Sharma et al., 2016). Five of the studies reviewed show mixed results, where there was either no detected effect (Brunt & Bowblis, 2014; Burke et al., 2016; van Poelgeest et al., 2015; Yanamadala et al., 2016) or a trade-off between lower mortality and greater readmissions (Lee, Kuo, & Goodwin, 2013).

Effects of EHRs on Cost of Care

When reviewing the published research from the last five years that show the effects of EHRs on the cost of care, there are few studies that address this aspect directly. In fact, upon review, there were only two studies found in the last five years that discuss the cost of care (Sharma et al., 2016; Teufel et al., 2012). It has been previously discussed that lawmakers had hoped that EHRs would ultimately reduce the cost of care (Teufel et al., 2012). As it turns out, the two recent studies that directly incorporate the notion of cost of care and EHR implementation found that costs have increased (Sharma et al., 2016; Teufel et al., 2012).

Sharma et al. (2016) was discussed in the last section when investigating EHR effects on quality, but the authors also measured the cost of care in addition to studying the effects on quality of care. Interestingly, the authors noted a significant difference between EHRs and other clinical information systems with respect to cost of care

(Sharma et al., 2016). They noted that EHRs correlate with increased costs while other clinical information systems decrease costs (Sharma et al., 2016). This study shows that there continues to be a complicated interplay between how certain types of clinical information systems have differing effects on various outcome variables at organizations and that implementing advanced healthcare IT systems may not necessarily reduce overall costs for healthcare organizations.

Additionally, Teufel et al. (2012) investigated EMR use in a hospital pediatric service setting. The EMR has been touted to reduce the cost and improve the safety of healthcare delivery in the United States (Teufel et al., 2012). Cost savings using EMRs have been projected at $81 billion each year (Teufel et al., 2012). There have been studies that looked at the adult population and EMR use, but the use of these systems in the pediatric service has not been evaluated (Teufel et al., 2012). This study incorporated data from the HCUP Kids Inpatient Dataset from 2009 and included 4,605,454 weighted discharges. It turns out that the use of the EMR in this study did increase safety for the patient but also increased the cost (Teufel et al., 2012). This translated to roughly a 7% increase in cost (Teufel et al., 2012). These findings, however, may be limited to the pediatric setting and may not generalize to other patient populations, as the data from this study primary included the pediatric patient population (Teufel et al., 2012).

Effects of EHRs on Efficiency

In this section, studies from the last five years will be examined, specifically with a focus on the effects of EHR use and the efficiency of healthcare services delivered. Twelve recent studies will be examined to show effects that clinical information systems and EHRs have on the efficiency of healthcare organizations. EHR use and healthcare service efficiency is one of the most studied aspects of EHR implementations. The following studies are arranged chronologically from the newest to the oldest, based on year of publication.

Schreiber and Shaha (2016) investigated a relatively novel view of EHRs, which was from the dimension of return on investment. Specifically, this study used the computer-based provider order entry (CPOE) functionality in EHRs as a determining factor that could affect length of stay, which is a commonly used proxy for efficiency in healthcare organizations (Schreiber & Shaha, 2016). Case Mix Index (CMI) was also used as a variable in the analysis (Schreiber & Shaha, 2016). This study used data from a single community hospital in the U.S. (Schreiber & Shaha, 2016). The findings of this study indicated that there is a relationship between CPOE functionality use and length of stay, at least within this community hospital (Schreiber & Shaha, 2016). For example, a higher CPOE use correlated with a lower length of stay (Schreiber & Shaha, 2016). Additionally, this study adds to the body of knowledge that even individual EHR functions can affect the efficiency of healthcare organizations (Schreiber & Shaha, 2016).

Additionally, Bae and Encinosa (2016) investigated the effect that EHRs have on workload and efficiency in the primary care setting. These authors noted an interesting trend and split among younger and older physicians. For example, the authors found that younger physicians that use EHRs had lower weekly patient volume, while older physicians had higher weekly patient volume (Bae & Encinosa, 2016). This certainly seems counterintuitive when it is generally well known that younger generations adapt to technology faster than older generations. In this scenario, the opposite was shown to be significant. The authors noted that this counterintuitive difference may be more about the clinical experience of the physician than how generally adept they are with technology (Bae & Encinosa, 2016).

Along a slightly different investigative path, Lee and Choi (2016) investigated the relationship between Healthcare Information Technology spending and organizational revenue. The HITECH Act of 2009 offered healthcare organizations large incentives for implementing and meaningfully using healthcare technology (Lee & Choi, 2016). These incentives can translate into between $2 million and $10 million for providers (Lee & Choi, 2016). These healthcare IT systems can help the hospital increase its revenue through several means, including elimination of redundant tests, reduction in length of stay, and lower administrative costs (Lee & Choi, 2016). The authors found that a doubling of healthcare IT spending correlated with a 4.7% increase in inpatient revenue and a 5.8% increase in outpatient revenue (Lee & Choi, 2016).

Of course, there is research to support the notion that EHRs can reduce efficiency in certain scenarios. For example, Lam, Lee, & Chen (2015) investigated the post-EHR throughput of an Ophthalmology department at an academic health system. The researchers noted a significant reduction (16.9%) in patients seen in that department after the implementation of an EHR (Lam, Lee, & Chen, 2015). This study followed eight physicians and covered a four-month period before EHR implementation and a four-month period after EHR implementation (Lam, Lee, & Chen, 2015). The researchers also noted that support staffing levels were relatively unchanged during the analysis periods (Lam, Lee, & Chen, 2015).

Adler-Milstein, Everson, and Lee (2015) sought to evaluate hospital outcomes and performance after EHR adoption, five years into the HITECH Act of 2009. This study was published in 2015, but used data from 2008-2012 (Adler-Milstein, Everson, & Lee, 2015). The researchers analyzed time-related effects of EHR adoption, comparing two different time periods (Adler-Milstein, Everson, & Lee, 2015). The first period was 2008 and 2009, while the second period was 2010 and 2011 (Adler-Milstein, Everson, & Lee, 2015). The authors compared the two periods that represent a pre-EHR adoption period and a post-EHR adoption period (Adler-Milstein, Everson, & Lee, 2015). The findings of this study indicated that there is a positive correlation between EHR adoption and process adherence and patient satisfaction, but there was not a significant identified correlation with efficiency (Adler-Milstein, Everson, & Lee, 2015). The authors noted that EHR adoption may standardize documentation and processes but may not positively affect healthcare service efficiency (Adler-Milstein, Everson, & Lee, 2015).

As noted previously in the quality section, Gholami et al. (2015) showed that there were positive effects on quality, specifically mortality, with the use of information technology, but there is also an efficiency factor that should be stated. For example, the authors found that there was a relationship between the use of information technology and efficiency but it was not a simple linear relationship (Gholami et al. (2015). The authors pointed out that there is a certain level of information technology use that changes the efficiency factor from negative to positive for the organizations. (Gholami et al., 2015). This is remarkable in that it would seem to suggest that healthcare leaders should invest not just in pockets of health IT systems, but move the organization in a distinctly technology-centered direction to obtain the greatest benefits.

Additionally, Tall, Hurd, and Gifford (2015) evaluated the impact of EMR systems on Emergency Department efficiency. The use of EMR systems has been fueled by large amounts of incentive payments to healthcare organizations in recent years (Tall, Hurd, & Gifford, 2015). Some of the disadvantages of EMR use included the time needed to document in the system, various interruptions in the clinical workflow, and system errors (Tall, Hurd, & Gifford, 2015). These systems may also create an overdependence on technology and change clinical communication practices, which may lead to a host of different unintended errors in care (Tall, Hurd, & Gifford, 2015). The authors found that post-EMR implementation the Emergency Department length of stay, which can be thought of as a proxy for efficiency, was not significantly affected by this new system (Tall, Hurd, & Gifford, 2015). In addition, there was only minimal clinical impact and workflow disruption due to this system being installed and used (Tall, Hurd, & Gifford, 2015).

Brunt and Bowblis (2014) studied EHR efficiency in primary care setting. As previously noted in the quality section, there were no differences in the quality of care due to EHRs, but there was a difference in the efficiency of care as measured by patient throughput (Brunt & Bowblis, 2014). For example, fewer patients were seen in the post-EHR practice as opposed to prior to the use of the EHR (Brunt & Bowblis, 2014). Unlike the Bae and Encinosa (2016) study that differentiated between older and younger physicians with respect to patient throughput, this study did not make this breakout for this user population, but they did note that older physicians, as measured by years in their practice, were less likely to have adopted EHRs than younger physicians.

Yang et al. (2014) continued to build upon the base of existing literature about EMR’s effect on the efficiency and clinical outcomes in hospitals. This study was performed at a single hospital in China and covers a pre-EMR and post-EMR timeframe from 2004 to 2012 (Yang et al., 2014). The data collected included several different clinical departments within the hospital and included several different disease conditions as well (Yang et al., 2014). The results of the study showed several interesting details about the teaching hospital's experience with their EMR implementation. For example, the authors noted that patient length of stay was reduced significantly after the EMR implementation (Yang et al., 2014). This study is unique in that it included an analysis of EMR implementation on length of stay at a department level as opposed to the organizational level (Yang et al., 2014).

As briefly discussed previously in the EHR effects on quality section, Lee, Kuo, and Goodwin (2013) found a reduction in one of the common efficiency proxy indicators used by organizations—length of stay. In the study, the researchers found a modest reduction in length of stay, only 0.11 days less than non-EHR organizations (Lee, Kuo, & Goodwin, 2013). Though this effect was statistically significant, it was not clear how much this would affect the operation of the organizations implementing EHRs. The authors noted the reduction in length of stay is clinically significant, but do not elaborate on this point in detail (Lee, Kuo, & Goodwin, 2013). Additionally, the authors noted that this reduction in length of stay may increase the rate of readmission (Lee, Kuo, & Goodwin, 2013). It is interesting that this potential unintended side effect of EHRs could make organizations less efficient and lower quality by increasing readmissions.

Henning, Horng, and Sanchez (2013) looked at the productivity of Emergency Department residents when using the Electronic Health Record (EHR). The analysis was done both pre- and post-EHR implementation (Henning, Horng, & Sanchez, 2013). The data was collected from the institution's information systems and included groups of residents that charted on paper and those that charted electronically after the system's implementation (Henning, Horng, & Sanchez, 2013). The charting process was apparently used as a proxy for productivity in this department (Henning, Horng, & Sanchez, 2013). The data that was analyzed included shift data pre- and post-EHR implementation, which entailed 1,259 shifts pre-EHR and 1,146 shifts post-EHR (Henning, Horng, & Sanchez, 2013). The results of the analysis indicated that there was no significant difference in the efficiency, as measured by electronic charting, post-EHR implementation (Henning, Horng, & Sanchez, 2013). This is contrary to popular belief that EHRs tend to increase the time to document and, therefore, slow down work and lower efficiency (Henning, Horng, & Sanchez, 2013).

Additionally, Huerta et al. (2013) looked at the implementation of EHRs and their effect on healthcare delivery in the U.S. The authors specifically looked at the efficiency of the healthcare organization post-EHR implementation (Huerta et al., 2013). The data from this study came from the American Hospital Association annual survey from 2006 to 2008 (Huerta et al., 2013). This study utilized a rather unique method of measuring organization efficiency—the Malmquist TFP, or Total Factor Productivity (Huerta et al., 2013). The findings of the study indicated that those organizations that have implemented EHRs have lower productivity, as measured by Malmquist TFP, than those organizations that have not implemented EHRs (Huerta et al., 2013). The authors also suggested that any savings associated with EHRs may not be seen until sometime after the EHR system has been implemented, due to this drop in initial productivity (Huerta et al., 2013).

EHR Research Sources of Data and Types of Analyses

The sources of data vary between primary sources of data (e.g., EHRs) and secondary sources of data which can include various national surveys and state or federal government data submissions. For these recent studies, there is almost an even split between primary and secondary sources, though a few more studies use secondary sources than primary. For example, seven of the examined studies used EHRs as their primary source of data for analysis (Ben-Assuli, Shabtai, & Leshno, 2013; Burke et al., 2016; Henning, Horng, & Sanchez, 2013; Lam, Lee, & Chen, 2015; Schreiber & Shaha, 2016; Tall, Hurd, & Gifford, 2015; Yang et al., 2014). Additionally, eleven of the examined studies used secondary sources of data which range from state and federal data submissions, national surveys, and various other industry surveys (Adler-Milstein, Everson, & Lee, 2015; Bae & Encinosa, 2016; Brunt & Bowblis, 2014; Gholami, Añón Higón, & Emrouznejad, 2015; Huerta et al., 2013; Lee & Choi, 2016; Lee, Kuo, & Goodwin, 2013; Sharma et al., 2016; Teufel et al., 2012; van Poelgeest et al., 2015; Yanamadala et al., 2016).

When further examining the date ranges collected from the various sources, as this is relevant to recent healthcare reform legislation, the data used is remarkable in that even recently published studies use data from well in the past, often beginning prior to healthcare reform legislation taking effect. For example, studies published in 2016 had ranges of data from 2006 to 2014 (Bae & Encinosa, 2016; Lee & Choi, 2016; Schreiber & Shaha, 2016; Sharma et al., 2016; Yanamadala et al., 2016). Studies published in 2015 had ranges of data from 2004 to 2014 (Adler-Milstein, Everson, & Lee, 2015; Gholami, Añón Higón, & Emrouznejad, 2015; Lam, Lee, & Chen, 2015; Tall, Hurd, & Gifford, 2015; van Poelgeest et al., 2015). Studies published in 2014 had ranges of data from 2004 to 2012 (Brunt & Bowblis, 2014; Yang et al., 2014). Studies published in 2013 had ranges of data from 2000 to 2011 (Ben-Assuli, Shabtai, & Leshno, 2013; Henning, Horng, & Sanchez, 2013; Huerta et al., 2013; Lee, Kuo, & Goodwin, 2013). The one study from 2012 that was evaluated had data that was from 2009 (Teufel et al., 2012).

The types of analyses used in evaluating EHRs and their effects on organizations varied as well. For example, some type of regression was the primary algorithm of choice for most researchers, with nine of the studies utilizing it some fashion (Bae & Encinosa, 2016; Ben-Assuli, Shabtai, & Leshno, 2013; Brunt & Bowblis, 2014; Henning, Horng, & Sanchez, 2013; Lee, Kuo, & Goodwin, 2013; Schreiber & Shaha, 2016; Teufel et al., 2012; Yanamadala et al., 2016; Yang et al., 2014). After regression, a form of groups comparison was the next most utilized algorithm with four studies. The groups comparison algorithms included t-tests, ANOVA, ANCOVA, etc. (Burke et al., 2016; Huerta et al., 2013; Lam, Lee, & Chen, 2015; Tall, Hurd, & Gifford, 2015). The remaining group of algorithms included some not commonly encountered in recently studies in this research area, including generalized estimation equation, chi-square, and data envelopment analysis (Lee & Choi, 2016; Sharma et al., 2016).

Teaching Hospitals versus Non-Teaching Hospitals

In addition to looking at the overall mixed effects of EHR adoption and use in the healthcare industry, it is important to also look at hospital type in similar dimensions. The teaching status of hospitals, and how it affects these dimensions of healthcare service delivery, has been studied both in this nation and internationally. For this literature review, the same dimensions of analysis will be used in this section as in the previous section: (1) the effects on the quality of service delivery due to hospital teaching status, (2) the effects on the cost of care due to hospital teaching status, and (3) the effects on the efficiency of the healthcare organization due to hospital teaching status. The studies examined show mixed results as they relate to these three dimensions of healthcare services and hospital teaching status.

The first dimension examined is the effects on the quality of service delivery due to hospital teaching status. In this dimension, there are studies that show that teaching hospitals have decreased mortality for several different conditions and patient populations (Dolmatova et al., 2016; Hansen, Fleischman, Meckler, & Newgard, 2013; Hyder, Sachs, Ejaz, Spolverato, & Pawlik, 2013). There is also research that failed to prove an association between teaching status and outcomes for a certain condition (Sandhu et al., 2013). There is also research that shows that hospital teaching status is associated with more hospital readmissions (i.e., lower quality; Chin, Wilson, Bang, & Romano, 2014).

The second dimension examined is the effects on the cost of care due to hospital teaching status. In this dimension, there is an absence of studies that show a clearly positive effect on the cost of care of teaching hospitals. Over the years, there were many studies that show a mixed effect, such as lower costs in one area while no differences in others (Chin, Wilson, Bang, & Romano, 2014; Hartley, Markowitz, & Komaroff, 1989; Medin et al., 2011; Rosko, 2004). Historically, there are several studies that show that teaching hospitals cost more, some showing a 10% increase while others are reporting a 30% increase over non-teaching hospitals (MacKenzie, Willan, Cox, & Green, 1991; Williams, Matthews, & Hassan, 2007).

The third dimension examined is the effects on the efficiency of the healthcare organization due to hospital teaching status. In this dimension, there is research that shows a positive effect on efficiency due to teaching status (Chin, Wilson, Bang, & Romano, 2014; Hyder, Sachs, Ejaz, Spolverato, & Pawlik, 2013; Szekendi et al., 2014). There is also older research that shows that teaching hospitals can become more efficient under the right kinds of conditions when required (Rosko, 2004). There are also studies that show the teaching status negatively affects efficiency (Lobo, Ozcan, Lins, Silva, & Fiszman, 2014; Williams, Matthews, & Hassan, 2007).

The data associated with the studies listed in this section vary widely. For example, there are studies that have data going as far back as 1982. Most of the studies in this section have data between 2000 and 2007, with a few studies that have data inclusive of 2013 and 2014. Overall, most these studies were prior to the HITECH Act of 2009 and generally do not break out Academic Medical Centers from the larger superset of teaching hospitals.

Teaching Hospital Effects on Quality

In this section, studies from the last five years will be examined, specifically with a focus on the effects of teaching status and the quality healthcare services delivered. Eleven recent studies will be examined to show the effect that the teaching status of hospitals has on service delivery. The studies are arranged chronologically from the newest to the oldest, based on year of publication.

Sheetz, Dimick, and Ghaferi (2016) conducted a study that looked at failure to rescue rates after surgery. The researchers found that several factors, including teaching status, offered advantages to patients after high-risk surgery (Sheetz, Dimick, & Ghaferi, 2016). This study was conducted based on MEDPAR and AHA survey data and covered the years from 2007 to 2010 (Sheetz, Dimick, & Ghaferi, 2016). The authors noted that although factors such as advanced technology and teaching status offered advantages to patients, other factors such as organizational culture may play large roles in patient outcomes as well (Sheetz, Dimick, & Ghaferi, 2016).

Similarly, Dolmatova et al. (2016) found advantages for teaching hospitals with respect to patient mortality. Specifically, the researchers noted a lower mortality (9% improvement odds) for cardiac arrest patients in teaching hospitals (Dolmatova et al., 2016). The authors also noted that this increased survivability may be attributed to advanced procedures performed at teaching hospitals that patients may not receive at non-teaching hospitals (Dolmatova et al., 2016). This study used data from the National Inpatient Sample (NIS) and covered the years from 2008 to 2012 (Dolmatova et al., 2016). In addition to lower mortality, the authors noted effects on cost and efficiency (Dolmatova et al., 2016). These effects will be outlined in the following appropriate sections.

In contrast to the previous study, Zafar et al. (2015) investigated the link between teaching status and the effects on quality, cost, and efficiency and found no clinically significant difference in mortality. This study also incorporated NIS data for adults and covered the years from 2007 to 2011 (Zafar et al., 2015). This is an interesting distinction as Dolmatova et al. (2016) found that there was lower mortality at teaching hospitals for cardiac arrest patients. The authors of this study looked specifically for patient outcomes of emergency general surgery (Zafar et al., 2015).

Another study that showed that teaching hospitals have lower mortality than non-teaching hospitals is that of Bir, Maiti, Ambekar, and Nanda (2015). Bir et al. (2015) noted that the odds of death and the odds of an adverse outcome at discharge were significantly lower at teaching hospitals than non-teaching hospitals (Bir et al., 2015). This study also utilized NIS data and included the years from 2003 to 2010 (Bir et al., 2015). Although the authors mentioned teaching status, the primary focus of the study was on different characteristics of patients and hospitals and focused solely on epidural hematoma (Bir et al., 2015).

Continuing in the vein of analysis of teaching hospital effects on quality, Nandyala et al. (2014) also studied the teaching hospitals versus non-teaching hospitals for lumbar spine surgery patients. When it comes to the quality of healthcare services at teaching hospitals, the authors noted that teaching hospitals were not correlated with greater mortality for patients in the hospital (Nandyala et al., 2014). In this study, there were more complications noted in teaching hospitals as opposed to non-teaching hospitals but this did not appear to have a significant effect on mortality (Nandyala et al., 2014). This study also used NIS data and covered the years from 2002 to 2011 (Nandyala et al., 2014).

In similar fashion, but more favorable than the previous study, Lai, Lin, and Du (2014) found that teaching hospitals had more favorable outcomes than non-teaching hospitals with respect to patients with ruptured aneurysms. For example, these authors noted that the likelihood of death (in-hospital) was decreased by 31% in teaching hospitals compared to non-teaching hospitals (Lai, Lin, & Du, 2014). This study also incorporated NIS data and covered the years from 2001 to 2010 (Lai, Lin, & Du, 2014).

The authors also noted that there could be correlation between teaching status and the volume of procedures performed, meaning, that the lower mortality may be more associated with higher volumes than teaching status itself (Lai, Lin, & Du, 2014).

Chin et al. (2014) conducted a study that looked at patient outcomes based on whether there was a preceptor involved in the patient’s care. Some of the outcomes that were investigated included the readmission rate, the length of stay, and the costs associated with the care (Chin et al., 2014). The study was conducted in a single teaching hospital in the U.S., based on that institution’s EHR clinical encounter data (Chin et al., 2014). The results of the study indicated that those patients that had preceptor encounters with clinicians had a higher readmission rate, a reduced length of stay, and lower hospitalization costs (Chin et al., 2014). The total inpatient costs within a month of discharge were similar for both groups, however (Chin et al., 2014).

Another patient population that was studied for quality differences between teaching and non-teaching hospitals were those patients that received percutaneous coronary intervention (Sandhu et al., 2013). The data for this study came from the state of Michigan and covered the years from 2007 to 2009 (Sandhu et al., 2013). The authors noted that the patient outcomes were mixed. For example, in this patient population, teaching hospitals were shown to have a higher rate of complications, while non-teaching hospitals were shown to have an increased risk of emergency coronary artery bypass grafting (Sandhu et al., 2013). Additionally, though these two differences were apparent in the analysis, the authors found that patients had similar general outcomes between teaching and non-teaching hospitals (Sandhu et al., 2013).

Hyder et al. (2013) were primarily investigating the differences in length of stay and mortality for patients that have a type of surgery that can include the pancreas and liver. The results of this study revealed that those patients undergoing these procedures associated with this type of surgery have better outcomes at academic hospitals as opposed to non-academic hospitals (Hyder et al., 2013). In fact, the researchers found that patients were 32% more likely to die at non-academic hospitals as compared to academic hospitals for this surgery, though the researchers did mention most of the mortality difference was based on the procedure volume differences between academic and non-academic hospitals (Hyder et al., 2013). They also noted that academic hospital patients had a shorter length of stay, and had fewer complications (Hyder et al., 2013).

Similar to some of the previous studies investigated, Fineberg et al. (2013) noted that patient complications were higher at teaching hospitals, specifically procedure-related complications. The patient subset analyzed in this study were cervical spine surgery patients (Fineberg et al., 2013). Data for this study again came from the NIS data set and included the years from 2002 to 2009 (Fineberg et al., 2013). The authors noted that hospital mortality for these patients was higher at teaching hospitals than non-teaching hospitals, but found that comorbidities and patient age were more predictive of mortality than hospital teaching status (Fineberg et al., 2013).

Reinforcing the notion that patient outcomes may be nuanced and conflicting in teaching hospitals, Carretta et al. (2013) found that mortality from congestive heart failure was higher at teaching hospitals. Interestingly, the authors found teaching hospitals had lower mortality 30 days after discharge (Carretta et al., 2013). Additionally, the analysis revealed that larger hospitals had higher mortality rates for congestive heart failure, stroke, and 30 days after discharge (Carretta et al., 2013). The data from this study came from the state of Florida and was from 2008 (Carretta et al., 2013).

Teaching Hospital Effects on Cost of Care

In this section, studies from the last five years will be examined, specifically with a focus on the effects of teaching status and the cost of healthcare services delivered. Seven recent studies will be examined to show the effect that the teaching status of hospitals has on service delivery cost. The studies are arranged chronologically from the newest to the oldest, based on year of publication.

As outlined in the previous section, research by Dolmatova et al. (2016) noted not just effects on quality of care in teaching hospitals but also effects on cost of care. These authors noted a significant increase in cost of care for patients treated for cardiac arrest at teaching hospitals (Dolmatova et al., 2016). This study revealed that the mean cost of teaching hospitals was about 62% more than non-teaching hospitals as measured by hospitalization costs for cardiac arrest patients (Dolmatova et al., 2016). The authors mentioned that teaching status itself was found to be a reliable predictor of greater length of stay and greater total cost (Dolmatova et al., 2016).

Zafar et al. (2015) studied emergency general surgery patients based on the NIS data set and found that teaching hospitals were on average $542 per hospital stay more expensive than non-teaching hospitals. This study confirmed other research that teaching hospitals are generally more expensive than non-teaching hospitals. Although this cost is higher for teaching hospitals than non-teaching hospitals, it may not be a relevant difference as noted by the authors (Zafar et al., 2015). The researchers also noted that there are reasons why teaching hospitals are often more expensive than non-teaching hospitals (Zafar et al., 2015). For example, teaching hospitals often receive the sickest patients, which require more diagnostic tests, increased nursing supervision and staffing, etc. (Zafar et al., 2015). The researchers mentioned that the general label of teaching hospital does not necessarily mean that all services provided by the facility involve trainees, and this distinction could lead to ambiguity when comparing facilities (Zafar et al., 2015).

With respect to cost differences between teaching and non-teaching hospitals, Bir et al. (2015) noted that there were no significant differences between these two types of organizations, at least for epidural hematoma patients. The authors of this study only mentioned there is not a significant difference in hospitalization costs, so it could be assumed they mean there is no statistically significant difference in costs between teaching and non-teaching hospitals. As outlined in the previously study by Zafar et al. (2015), it is possible that there could be a statistically significant difference in costs without there being a clinically significant difference in costs. It appears, at least for epidural hematoma patients, there is no statistically significant difference in cost (Bir et al., 2015). This study included NIS data for the years from 2003 to 2010 (Bir et al., 2015).

A study that was particularly relevant to this research was from Adrados et al. (2015). The authors of this study investigated the cost of care across New York State hospitals for total joint arthroplasty for the years from 2009 to 2011 (Adrados et al., 2015). Though the authors were primarily investigating the beneficiary health status, they did note in the analysis that teaching status, among other variables, did not appear to affect the costs of total joint arthroplasty patients (Adrados et al., 2015). The data for this study primarily came from New York State's hospital inpatient cost transparency database (Adrados et al., 2015).

The overall greater cost of care at teaching hospitals was reinforced by a recent study from Nandyala et al. (2014). In this study, the authors noted an increased hospital cost of nearly $3,000 for lumbar surgery patients at teaching hospitals (Nandyala et al., 2014). As previously mentioned, the analysis showed that there were greater complications for patients at teaching hospitals versus non-teaching hospitals, and this may have contributed to some of the cost increase, but the authors specifically list older patients with more comorbidities as a likely explanation of the increased cost (Nandyala et al., 2014). The analysis revealed that teaching hospitals did have older patients for this type of surgery but it was only a difference of about one year, where teaching hospital patients were on average 56.7 years and non-teaching hospitals patients were on average 55.6 years old (Nandyala et al., 2014). While this difference may be statistically significant, it does not seem clinically significant. Additionally, the incidents of several serious complications were significantly higher at teaching hospitals (Nandyala et al., 2014).

In contrast to other similar studies, Chin et al. (2014) found that teaching services within a single academic hospital had lower initial hospitalization costs but did not have statistically significantly different costs when considering hospital costs including 30 days after discharge. As was discussed in the previous section for this study, the higher rate of readmissions for teaching services may contribute to similar overall hospitalization costs between teaching and non-teaching services (Chin et al., 2014). This study used data from a single hospital's EHR and covered the years from 2008 to 2012 (Chin et al., 2014).

Fineberg et al. (2013) found that teaching hospitals incurred higher costs than non-teaching hospitals. For example, in this study of cervical spine surgery patients, the authors found that teaching hospitals had mean costs roughly $500 higher than non-teaching hospital (Fineberg et al., 2013). The median cost difference was more minor and only reflected a cost of roughly $130 higher (Fineberg et al., 2013). The authors further broke down different groupings of cervical surgery types to show the cost differences and the statistically significant cost differences all have higher costs for teaching hospitals (Fineberg et al., 2013).

Teaching Hospital Effects on Efficiency

In this section, studies from the last five years will be examined, specifically with a focus on the effects of teaching status and the efficiency of healthcare services delivered. Nine recent studies will be examined to show the effect that the teaching status of hospitals has on service delivery efficiency. The studies are arranged chronologically from the newest to the oldest, based on year of publication.

The study performed by Dolmatova et al. (2016) has been discussed in the previous sections around the quality of care and cost of care differences in teaching hospitals. In this section, this study will be discussed with respect to efficiency differences in teaching hospitals as measured by length of stay (Dolmatova et al., 2016). Dolmatova et al. (2016) noted that cardiac patients in teaching hospitals experienced longer lengths of stay than those patients in non-teaching hospitals. The median length of stay for teaching hospitals was five days and it was four days for non-teaching hospitals (Dolmatova et al., 2016).

Another study that investigated the differences in efficiency between teaching and non-teaching hospital was performed by Zafar et al. (2015). In this study, the researchers found no clinically significant difference in the efficiency of teaching hospitals versus non-teaching hospitals (Zafar et al., 2015). For example, the authors noted an average difference of only 0.19 days (Zafar et al., 2015). While this difference may be statistically significant, it most likely is not clinically significant and the authors call this out in their research as well (Zafar et al., 2015).

Szekendi et al. (2014) looked at how academic medical center CEOs viewed the boards that govern their organization, and that they ultimately report to. There are six governing best practices that boards and leaders in those organizations should adhere to in order to promote the most efficient governance process (Szekendi et al., 2014). This study included a survey of all 105 academic medical center CEOs in the United HealthSystem Consortium (UHC) group (Szekendi et al., 2014). The results of the analysis showed that the highest performing organizations adhered to all six best practices of governance (Szekendi et al., 2014). The authors also noted that the board should focus on member education and on quality improvement initiatives, even if it is closely using all six best practices (Szekendi et al., 2014). In addition, it was noted that CEO and board assessment (or self-assessment) processes were lacking significantly even in the highest performing organizations (Szekendi et al., 2014).

Efficiency, as often measured by length of stay in the hospital, was also analyzed by Nandyala et al. (2014) for teaching versus non-teaching hospitals. The authors noted that for lumbar spine surgery patients, teaching hospitals had longer hospitalizations and more complications (Nandyala et al., 2014). The authors primarily attributed this to the more complicated procedures performed at teaching hospitals and the generally older population serviced by teaching hospitals (Nandyala et al., 2014). The mean length of stay at teaching hospitals was certainly higher at 3.7 days versus 3.0 days at non-teaching hospitals and was statistically significant (Nandyala et al., 2014).

Incorporating analysis from outside the U.S., Lobo et al. (2014) studied 104 teaching hospitals in Brazil using data from 2007. The authors were primarily investigating efficiency in these hospitals and found that the primary predictors of hospital efficiency were size, high teaching intensity, and low teaching dedication (Lobo et al., 2014). This study also incorporated several environmental and legislative components to better understand the operating environments of these hospitals (Lobo et al., 2014). The authors also noted some of the societal benefits of teaching hospitals, even though teaching hospitals have higher costs (Lobo et al., 2014).

As discussed in the quality effects section above, Lai, Lin, and Du (2014) showed that teaching hospitals have a lower in-hospital mortality for ruptured aneurysms than non-teaching hospitals. The authors also significantly noted that the lower mortality at teaching hospitals for this patient subset did not come at the cost of a longer length of stay (Lai, Lin, & Du, 2014). For example, the mean teaching hospital length of stay was 20.4 days and the mean non-teaching hospital length of stay was 20.1 days with a p-value of .801 (Lai, Lin, & Du, 2014).

When comparing teaching-oriented hospital services to non-teaching hospital services, Chin et al. (2014) found that teaching services had a lower length of stay than non-teaching services. For example, the authors noted a length of stay of 5.63 days for academic-preceptor services and a length of stay of 5.50 days for hospitalist-preceptor services, while the hospitalist-only services had a length of stay of 6.06 days (Chin et al., 2014). The authors surmised that the trainees in the teaching services may be contributing to the lower length of stay and are discharging patients too early, which could also lead to greater readmissions (Chin et al., 2014).

Another study conducted by Hyder et al. (2013) showed that teaching hospitals had greater efficiency, as measured by length of stay, compared to non-teaching hospitals. The authors of this study looked at a subset of surgery patients (complex hepatopancreaticobiliary surgery) to evaluate teaching status on both length of stay and mortality measures (Hyder et al., 2013). For example, the authors noted that median length of stay for teaching hospitals was 7.7 days, compared to 8.6 days at non-teaching hospitals (Hyder et al., 2013). This difference of almost an entire day, in contrast to other studies that found statistically significant differences in lengths of stay, would seem to be clinically significant as well as statistically significant.

In contrast, Fineberg et al. (2013) noted that the mean length of stay was statistically significantly longer at teaching hospitals than non-teaching hospitals by 0.3 days. Though this is statistically significant, it is not clear if this difference is clinically significant. The median length of stay for these cervical spine surgery patients was not statistically different at 1.0 days for both types of hospitals (Fineberg et al., 2013). This trend where the mean length of stay was statistically significantly higher at teaching hospitals while the median length of stay was similar is present throughout the subgroups of cervical spine surgery patients in this study (Fineberg et al., 2013).

Teaching Hospital Research Sources of Data and Types of Analyses

The sources of data vary between primary sources of data, namely the organization's EHR, and secondary sources of data which can include various national surveys and state or federal government data submissions. For these recent studies, a large majority of the studies looking at teaching hospital effects used secondary sources as compared to primary sources. Fourteen studies used some type of secondary source, where seven of the fourteen used the National Inpatient Sample, and the remaining seven used various other registries and organizational surveys (Adrados et al., 2015; Bir et al., 2015; Carretta et al., 2013; Dolmatova et al., 2016; Fineberg et al., 2013; Hansen et al., 2013; Hyder et al., 2013; Lai, Lin, & Du, 2014; Nandyala et al., 2014; Navathe et al., 2013; Sandhu et al., 2013; Sheetz, Dimick, & Ghaferi, 2016; Szekendi et al., 2014; Zafar et al., 2015). Two of the studies investigated included primary sources from the actual organization, including EHRs (Chin et al., 2014; Lobo et al., 2014).

When further examining the date ranges collected from the various sources, as this is relevant to recent healthcare reform legislation, the data used is remarkable in that even recently pushed studies use data from well in the past, often beginning prior to healthcare reform legislation taking effect. For example, studies published in 2016 had ranges of data from 2008 to 2012 (Dolmatova et al., 2016; Sheetz, Dimick, & Ghaferi, 2016). Studies published in 2015 had ranges of data from 2003 to 2011 (Adrados et al., 2015; Bir et al., 2015; Zafar et al., 2015). Studies published in 2014 had ranges of data from 2001 to 2014 (Chin et al., 2014; Lai, Lin, & Du, 2014; Lobo et al., 2014; Nandyala et al., 2014; Szekendi et al., 2014). Studies published in 2013 had ranges of data from

1996 to 2010 (Carretta et al., 2013; Fineberg et al., 2013; Hansen et al., 2013; Hyder et al., 2013; Navathe et al., 2013; Sandhu et al., 2013).

The types of analyses used in evaluating teaching hospitals varied as well often included several different algorithms used to evaluate different types of variables. The following groups represent general themes, most studies used more than one type of analysis algorithm. Some form of regression was the most utilized algorithm, with twelve studies utilizing it in some form (Adrados et al., 2015; Bir et al., 2015; Carretta et al., 2013; Fineberg et al., 2013; Hansen et al., 2013; Hyder et al., 2013; Lai, Lin, & Du, 2014; Lobo et al., 2014; Nandyala et al., 2014; Navathe et al., 2013; Sandhu et al., 2013; Zafar et al., 2015). Groups comparison algorithms, such as t-tests and various ANOVA algorithms, were also heavily utilized by researchers to compare teaching services and organizations to non-teaching services and organizations (Adrados et al., 2015; Fineberg et al., 2013; Nandyala et al., 2014; Sheetz, Dimick, & Ghaferi, 2016). Various other types of analysis algorithms were also utilized by researchers to investigate other types of variables, these included data envelopment analysis, generalized estimation equation, chi-square, etc. (Bir et al., 2015; Chin et al., 2014; Dolmatova et al., 2016; Fineberg et al., 2013; Lobo et al., 2014; Nandyala et al., 2014; Sandhu et al., 2013; Szekendi et al., 2014; Zafar et al., 2015).

Summary

In this review of current literature involving EHR implementation and teaching status effects on the quality, cost, and efficiency of healthcare services, there many conflicting results. There is not a clear pattern of EHR effects on quality as there are studies that show these systems improve quality, lower quality, and do not affect quality.

There were relatively few studies that investigated EHR effects on cost of care, but those showed that EHRs increase the cost of care, overall. Efficiency of healthcare service delivery was the most studied aspect of EHR implementation. The results of these studies were largely mixed in this category as well. Based on the extant literature, the implementation of EHRs is highly complicated process that appears to have varied and conflicting effects on healthcare organizations.

In similar fashion, the effects of teaching status on the quality, cost, and efficiency of healthcare services delivered are also highly variable. When investigating the effect on the quality of healthcare services, the extant literature from the last five years is similarly conflicting. There are studies that show lower quality, no effect on quality, and higher quality at teaching hospitals. When investigating the effects on the cost of healthcare services at teaching hospitals, the literature largely revealed higher costs at these organizations, or no significant difference. The efficiency of healthcare service delivery at teaching hospitals was also variable, as there were both longer and shorter lengths of stay noted, or no significant difference.

As the studies investigated included data prior to the HITECH Act of 2009 going into effect or shortly after, it is important to continue to investigate the effects of EHRs on healthcare organizations as they stabilize their use of these information systems. Additionally, the investigation of possible interaction effects between EHRs and teaching hospitals on the quality, cost, and efficiency of service delivery would be worthwhile. Obtaining more clarifying data on the how EHR use and teaching status affect organizations may help answer these important questions and direct future research.

Chapter 3: Research Method

Recent U.S. healthcare legislation reform has created large incentives for clinical information system adoption, specifically electronic health records (Lee & Choi, 2016). The HITECH Act provided healthcare organizations with tens of billions of dollars in incentives over the course of a decade to implement and use EHRs meaningfully (Lee & Choi, 2016). Though the U.S. healthcare enterprise is rapidly implementing EHRs and other clinical information systems due to large governmental incentives, the evidence to prove that these systems lower cost and increase clinical quality is conflicting and nuanced (Burke et al., 2016; Sharma et al., 2016; Tall et al., 2015; Yanamadala et al., 2016).

The teaching status of hospitals and its effect on hospital cost and efficiency has been studied over the last several decades (Rosko, 2004; Williams et al., 2007) but there are few recent studies evaluating these factors based on data after the recent healthcare reform legislation and corresponding EHR implementations at an organizational level (Chin et al., 2014; Dolmatova et al., 2016; Zafar et al., 2015). The importance of studying the effects of EHRs on organizations in the post-healthcare reform landscape has been identified as an area of needed research (Gholami et al., 2015).

The problem is that the effects of EHR implementations on hospitals have been varied and nuanced and that teaching hospitals have traditionally differed from other hospitals when it came to their service delivery. Research should be conducted to examine how EHRs may have affected teaching hospitals in ways different than non-teaching hospitals. By examining this potential distinction, healthcare professionals and lawmakers may be able to refine their application of this technology in these organizations and properly incentivize its use for the benefit of the patient, the hospital, and the nation.

The purpose of this quantitative correlational study is to examine the performance differences between teaching and non-teaching hospitals in the post-EHR implementation landscape, specifically investigating possible interaction effects between EHRs and hospital teaching status. This study also includes analyses that may help to confirm or disconfirm past research findings regarding the cost differences between teaching and non-teaching hospitals as well as potential quality and efficiency differences after the implementation of EHRs. This knowledge will help to establish whether EHRs have made a meaningful impact on the cost and efficiency of care (in addition to the quality of care) in teaching hospitals. There is also an attempt to re-establish the baseline cost differences between teaching and non-teaching hospitals post-EHR, where teaching hospitals are further stratified into minor and major teaching hospitals per guidance from previous research (Navathe et al., 2013).

The current analysis around EHRs, particularly with respect to their application within teaching hospitals, still has several unexplored frontiers. The United States is firmly on its journey of EHR adoption. Some research remains relatively ambiguous and conflicting when it comes to the larger picture of how EHRs affect hospitals (Burke et al., 2016; Sharma et al., 2016; van Poelgeest et al., 2015). Teaching hospitals, and the potential effects of EHR implementations on those organizations, have largely not been studied at organizational levels in the post-healthcare reform landscape. This study may help to add insight in this area of research.

This chapter will overview the research methods and design, the population description and sample, operational definition of the variables involved, data collection and analysis, assumptions, limitations, and ethical considerations of the study. With these aspects of the research outlined, the reader will better understand the methodology, opportunities, and limitations of this research. Based on this, future researchers could devise new experiments and analysis techniques to further refine and build upon this research.

Research Methods and Design

The research method and design for this study incorporated a two-way multivariate ANOVA (MANOVA) design. The two independent variables for this MANOVA test are EHR category (whether an EHR is present or not in each hospital), and the teaching category of the hospital (non-teaching, minor teaching, or major teaching hospital), based on previous research (Navathe et al., 2013). The dependent variables will include: acute myocardial infarction (AMI) mortality risk adjusted rate, heart failure mortality risk adjusted rate, pneumonia mortality risk adjusted rate, AMI total costs, heart failure total costs, pneumonia total costs, AMI length of stay, heart failure length of stay, and pneumonia length of stay consistent with analysis methods from previous research (Carretta et al., 2013; Chin et al., 2014; Dolmatova et al., 2016).

The MANOVA matrix will be created by processing the data files in several ways outlined later in this chapter. The final matrix included twelve columns and one row for each hospital in the study. The columns will include: (1) the hospital name, (2) teaching category (non-teaching, minor teaching, major teaching), (3) EHR category (no EHR, EHR), (4) AMI Risk Adjusted Rate, (5) Heart Failure Risk Adjusted Rate, (6) Pneumonia

Risk Adjusted Rate, (7) Pneumonia Total Costs, (8) Pneumonia Length of Stay, (9) Heart Failure Total Costs, (10) Heart Failure Length of Stay, (11) AMI Total Costs, (12) AMI Length of Stay.

A two-way multivariate ANOVA (MANOVA) design is the most appropriate to answer this type of question as the hospitals being evaluated are grouped in different ways. This grouping scheme (EHR or no EHR; non-teaching, minor teaching, or major teaching hospital) allows the inter-group differences to be evaluated statistically. These independent variables combined with several dependent variables allow the researcher to answer not only if the hospital groups have statistically significant differences between them but, by running post-hoc analyses, point to which combination of variables are significant along with their corresponding effect sizes. As this is essentially a groups comparison research design with largely continuous variables, other algorithms such as regression or chi-square would not allow the analysis of potential interaction effects between the two independent variables.

Population

The population of this study is essentially a group of New York State hospitals with 2014 data. The total population of potential hospitals is 203 based on the New York hospital data available but the final MANOVA matrix included 62 hospitals. This is due to various data not being available for all hospitals. Of the 203 potential hospitals, 173 are Not for Profit Corporations, 13 are Municipalities, five are State, five are County, five are Business Corporations, and two are Public Benefit Corporations. Of the final 62 hospitals ultimately included in the analysis, 50 are Not for Profit Corporations, eight are Municipalities, three are State, and one is County.

Sample

The sampling technique for this research study is simply based on availability of complete hospital data. Different states have different levels of access to various performance metrics for their hospitals and healthcare facilities. New York has already processed the data in such a way as to de-identify it for these purposes. In order to answer all of the research questions and hypotheses posed in this research, the New York state data, by itself, is not sufficient. This state's data must be combined with other data, namely that from CMS, in order to understand each organization's use of EHRs and their teaching status (as measured by their resident-to-bed ratio). The specifics of this analysis are explored in later sections.

The final number of hospitals that are available for analysis is 62. This is due to the processing that must occur, where hospitals are dropped from the total number as there are gaps in reporting data for each of the key variables. For this research, an argument can be made that missing data should disqualify a hospital and be dropped from the final MANOVA matrix. The primary reason for this is that the researcher would have impute a value into one or more of the variables for the algorithm to process that hospital. There are several strategies for imputation, but all could introduce bias into the analysis. If the final sample size is sufficiently large to perform the analysis and possibly detect the phenomenon of interest, dropping hospitals based on incomplete data can be justified.

Using a MANOVA (a priori sample size for MANOVA: special effects and interactions) with an effect size of 0.1, an alpha error probability of 0.05, a power rating of 0.8, with four groups, two predictors, and three response variables, G*Power shows a total sample size needed of 72 ("G*Power," 2016). Three response variables were chosen instead of the actual nine dependent variables due to the fact that three distinct two-way MANOVA tests were run, one test for each of the three dimension analyzed (quality, cost, and efficiency). The effect size chosen is set to detect small to medium effects and larger. The number of hospitals in the sample is smaller than what is needed to detect an effect size of 10%, but since the sample is actually ~25% of the total population (of New York State hospitals), a case can be made that a 25% sample rate is definitely large enough to detect even small statistically significant effect sizes, regardless of the actual number in the sample.

Materials/Instruments

No materials or research instruments are needed as the data for this study is publicly available. The two primary organizations that collected this data are the state of New York and the Centers for Medicare and Medicare Services (CMS). This data was primarily collected for performance purposes but is also available for research purposes in its de-identified form. The data files from New York state are available to the public from that state's data portal (https://data.ny.gov/) and the data files from CMS are similarly available to the public from the healthdata.gov data portal (https://www.healthdata.gov/).

Operational Definition of Variables

As previously mentioned, the two independent variables for these MANOVA tests are EHR category (whether an EHR is present or not in each hospital), and the teaching category of the hospital (non-teaching, minor teaching, or major teaching hospital), based on previous research (Navathe et al., 2013). Navathe et al. used the resident-to-bed ratio of each hospital to categorize them into non-teaching, minor teaching, and major teaching hospitals. The thresholds for this ratio were zero for non-teaching, greater than zero but less than 0.25 for minor teaching, and 0.25 or greater for major teaching (Navathe et al., 2013).

The dependent variables are: (1) AMI Risk Adjusted Rate, (2) Heart Failure Risk Adjusted Rate, (3) Pneumonia Risk Adjusted Rate, (4) Pneumonia Total Costs, (5) Pneumonia Length of Stay, (6) Heart Failure Total Costs, (7) Heart Failure Length of Stay, (8) AMI Total Costs, (9) AMI Length of Stay. The risk adjusted rates were used to accommodate for differences in patients' level of sickness and other factors to more fairly compare outcomes from patient to patient and facility to facility ("Introduction to measures of quality," 2014). The risk adjusted rates are published for each hospital in the New York State All Payer Inpatient Quality Indicators 2014 file. This file includes the risk adjusted rates for all New York state hospitals for a variety of conditions, though only AMI, Heart Failure, and Pneumonia were used.

The median total costs and mean lengths of stay for each hospital for AMI, Heart Failure, and Pneumonia were calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file. This file contains ~2.3 million inpatient discharges from all hospitals in New York State for the year 2014. From this file, AMI was filtered using the APR DRG description of "*ACUTE MYOCARDIAL INFARCTION*", which narrowed the discharges down to 16,559 inpatient discharges. Similarly, heart failure was filtered using the APR DRG description of "HEART FAILURE", which narrowed the discharges down to 54,218 inpatient discharges. Pneumonia was filtered using the CCS Diagnosis Description of "*PNEUMONIA*", which narrowed the discharges down to 46,113 inpatient discharges. From these filtered discharges, the median total costs and mean lengths of stay for each condition category were calculated.

EHR Category. Independent variable. The two possible categories are EHR or No EHR. This indicates whether the hospital has a certified EHR. The source of this data is the CMS Hospital Quarterly IPFQR Measures 2014 file.

Teaching Category. Independent variable. The possible categories are Non-Teaching, Minor Teaching, and Major Teaching. The thresholds for this ratio were zero for non-teaching, greater than zero but less than 0.25 for minor teaching, and 0.25 or greater for major teaching. The source of this data is the 2014 CMS Impact file.

AMI Risk Adjusted Rate. Dependent variable. The risk adjusted rates are published for each hospital in the New York State All Payer Inpatient Quality Indicators 2014 file. The risk adjusted rate is per 1,000 patient discharges.

Heart Failure Risk Adjusted Rate. Dependent variable. The risk adjusted rates are published for each hospital in the New York State All Payer Inpatient Quality Indicators 2014 file. The risk adjusted rate is per 1,000 patient discharges.

Pneumonia Risk Adjusted Rate. Dependent variable. The risk adjusted rates are published for each hospital in the New York State All Payer Inpatient Quality Indicators 2014 file. The risk adjusted rate is per 1,000 patient discharges.

Pneumonia Total Costs. Dependent variable. Pneumonia total costs were calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the CCS Diagnosis Description of "*PNEUMONIA*". Total costs are in dollars.

Pneumonia Length of Stay. Dependent variable. Pneumonia length of stay was calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the CCS Diagnosis Description of "*PNEUMONIA*". The length of stay is in days.

Heart Failure Total Costs. Dependent variable. Heart Failure total costs were calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the APR DRG description of "HEART FAILURE". Total costs are in dollars.

Heart Failure Length of Stay. Dependent variable. Heart Failure length of stay was calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the APR DRG description of "HEART FAILURE". The length of stay is in days.

AMI Total Costs. Dependent variable. AMI total costs were calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the APR DRG description of "*ACUTE MYOCARDIAL INFARCTION*". Total costs are in dollars.

AMI Length of Stay. Dependent variable. AMI length of stay was calculated based on the de-identified New York State Hospital Inpatient Discharges 2014 file using the APR DRG description of "*ACUTE MYOCARDIAL INFARCTION*". The length of stay is in days.

Data Collection, Processing, and Analysis

The data used in this analysis are publicly available from CMS and the New York State data portal and includes the following five files: (1) NYS All Payer Hospital Inpatient Discharges data for the year 2014, (2) CMS Hospital Quarterly Measures file from the Hospital Compare data for the year 2014, (3) CMS Impact file data for the year 2014, (4) NYS Health Facility General Information data, and (5) NYS All Payer Inpatient Quality Indicators data for 2014. The data files from New York state are available to the public from that state's data portal (https://data.ny.gov/) and the data files from CMS are similarly available to the public from the healthdata.gov data portal (https://www.healthdata.gov/).

Since these files contain data that are at different levels, a certain amount of data processing is needed to join the data together between the files and to allow for the creation of the two-way multivariate ANOVA (MANOVA) matrix for the ultimate analysis. The level of the data represents the lowest level of detail in each file. For example, some files have data at the hospital level, while other files have data at the individual inpatient discharge level. To analyze the data at the hospital level (since that is core of this research), rollups and aggregations must occur. All data preparation needed to create the final MANOVA matrix was done in KNIME (version 3.2.2).

The first file to be processed is the NYS All Payer Hospital Inpatient Discharges 2014 file which contains de-identified individual patient discharge summary data. The processing pipeline for this file includes the filtering of the three different inpatient conditions being studied (pneumonia, heart failure, and AMI) as previously mentioned. Once the filtering occurs, there are several other steps that must take place. For example, the financial data in the file must be changed from a set of characters to a number data type to facilitate the analysis by the MANOVA algorithm. Additionally, the mean length of stay and median total costs are calculated for each of those three conditions. The calculation of the median and mean values of these discharges is needed to gauge the cost and length of stay for these conditions at each hospital. These steps are done for each of the three disease conditions.

The next file to be processed is the CMS Hospital Quarterly Measures Hospital from the Hospital Compare data set. This file contains each hospital's response to CMS regarding their use of a certified EHR technology. There are three answers to this question—certified EHR, non-certified EHR, and paper or other form. This file contains data at the hospital level, so there is only one row for each hospital.

The third file to be processed is the 2014 CMS Impact file. This file contains hospital-level data such as the number of beds and the resident-to-bed ratio used in this analysis. As this analysis will join data from both state (New York) and federal (CMS) systems, there is a need to traverse different identifiers used by these different entities. For example, New York has an identifier that is applicable to the hospitals in the state (Facility ID). Similarly, CMS has an identifier that is applicable to all hospitals in the nation (Provider ID). Since there is a need to compare data from New York with CMS, a linking identifier must be used. Unfortunately, there is no known available crosswalk matrix to link Facility ID and Provider ID. The only way to effectively create a crosswalk is to manually compare the names of the hospitals. When comparing the names of the facilities between data from New York and data from CMS, there were several ambiguities and some facilities could not be identified with a high level of confidence. Of the hospitals that did have data in both state and federal systems and could be concretely identified as the same facility, a crosswalk of 78 hospitals was created. This crosswalk allowed the joining of the state and federal data at the hospital level or grain. The fourth file processed was the New York Health Facility General Information file which offered the Facility ID and the name of the hospital for the crosswalk.

The fifth file processed was the New York All Payer Inpatient Quality Indicators file. This file provided the risk adjusted rate for many disease conditions, but was filtered to only include the three disease conditions used in this analysis (pneumonia, heart failure, and AMI). This file also contained several years of data related to the quality indicators, so the filtering also only included 2014 data.

As these files are joined, the gaps in data for hospitals narrow down the number of hospitals included in the final analysis as the final MANOVA matrix needs data for all variables with no gaps or nulls. The joining of the data occurs in reverse order of the files listed. For example, for the fifth file, once the data is filtered, there are a total of 109 hospitals lists (where data was provided). The fourth, third, and second files are then joined along with the created Facility ID to Provider ID crosswalk. These three files, including the crosswalk, had a total of 106 hospitals. When the 109 hospitals from the fifth file was joined to the second, third, and fourth files based on Facility ID, only 62 hospitals were included. The reason is that only these 62 hospitals were included in both sets. Once these files were joined with the remaining first file, 62 hospitals remained as there was discharge data for all hospitals in the state, so no hospitals were dropped from the result set due to lack of data.

The final MANOVA matrix included twelve columns and one row for each hospital in the study. The columns will include: (1) the hospital name, (2) teaching category (non-teaching, minor teaching, major teaching), (3) EHR category (no EHR, EHR), (4) AMI Risk Adjusted Rate, (5) Heart Failure Risk Adjusted Rate, (6) Pneumonia

Risk Adjusted Rate, (7) Pneumonia Total Costs, (8) Pneumonia Length of Stay, (9) Heart Failure Total Costs, (10) Heart Failure Length of Stay, (11) AMI Total Costs, (12) AMI Length of Stay.

Assumptions

There are several assumptions to consider in this research proposal. For example, there are the standard statistical assumptions associated with the algorithm used. The MANOVA hypothesis test has several prerequisites about the structure of the data for statistical significance and effect sizes to be accurate. The primary effect of these statistical assumptions being violated is that the resultant analysis and hypothesis results will be unreliable. The results of the MANOVA may be statistically significant with large effect sizes, but these results may not actually be occurring in the data since the underlying structure of the data violates these assumptions. Prior to performing the MANOVA analysis, these statistical assumptions will be validated by several statistical tests.

Another assumption of this research is that the data is accurately reported by each of the healthcare organizations. For example, since there is blending of state-provided inpatient discharge data, which has a very fine grain, with aggregated organizational data reported to the state, where the state is computing the aggregated risk-adjusted rates for the disease conditions of interest. There is the potential that the inpatient discharges used by the state to calculate the risk-adjusted rates of these disease conditions differ from the inpatient discharges used in this research to calculate mean length of stay and median costs for each disease condition of interest. If this scenario introduces variance in the data, it would most likely manifest itself as faulty length of stay and faulty cost comparisons between each organization and each disease category. The analysis that compared the risk adjusted rates of these disease category mortalities would most likely be unaffected by this potential variance, however, as these variables come from pre-aggregated risk adjusted rates computed by the state.

A final assumption of this research is similar to the previous assumption in that the data used to determine EHR status and each organization's resident to bed ratio comes from CMS and dependent upon data sent to CMS by each organization. The categories for EHR status come from the CMS Hospital Quarterly IPFQR Measures file and has three potential response categories to the *Highest level typical use of an EHR system* measure: (1) Certified EHR Technology, (2) Paper or Other Form, and (3) Non-Certified EHR Technology. There is the potential for large differences in interpretation between organizations for each of these categories, particularly for organizations that have implemented part or most of an EHR system through subsequent, incremental implementations. This is a possible source of variance in the data. This analysis would also group Certified EHR Technology with Non-Certified EHR Technology as a single dichotomous variable (EHR vs Paper or no EHR). This grouping may also introduce some variance as well.

Similarly, the resident to bed ratio that is used to generate the categories of teaching hospitals is also received from CMS via the CMS Impact file. This variable is a derived value based on the number of residents at the organization and the licensed beds in the organization. Since New York State licenses inpatient beds based on a Certificate of Need (CON) construct, healthcare facilities must go through the state for number of beds it can operate at any one time (Jost, 2012). This process makes the number of beds rather accurate for New York state hospitals but potentially limits the comparison to hospitals in states without a CON requirement as those other states' hospitals may be more loose in their determination of hospitals beds.

Limitations

There are several limitations to this study. For example, this data primarily comes from New York State for the risk adjusted mortality rates for the disease conditions of interest, as well as the inpatient discharge level data for costs and lengths of stay for these disease conditions. Since the data primarily comes from a single state, and that state imposes certain regulations on its healthcare organizations not imposed by other states (e.g., CON constraints), the generalizability of these results may be limited to states with similar regulatory and patient population characteristics.

Delimitations

This analysis is limited to New York State hospitals and is based on adult inpatient discharges for the year 2014. The ultimate findings must be viewed through this lens. For example, outpatient discharges and inpatient discharges of children are not included in the data set and any findings cannot be generalized to those populations. Also, as this data only includes data from New York, generalizability to other states or nations may not be appropriate.

Ethical Assurances

As this data is de-identified by CMS and New York State as well as publicly available, there are no ethical considerations related to its collection or use. Though there are no human participants involved in this research, certain other ethical aspects of this research should be considered. For example, the sample size and the analysis directly relate to this research’s findings. If the sample size is too small, the analysis may not be able to detect the potential phenomenon of interest. Since the size of the sample is such that only small to medium sized effects and larger can be detected, substantial care should be taken when performing the statistical analysis.

In order to facilitate transparency in data preparation and the analysis, Chapter 4 will outline the data preparation steps for each of the MANOVA tests. The data is publicly available at the locations shared earlier in this chapter. The source data, combined with the data preparation and analysis steps in Chapter 4, with allow other researchers to possibly recreate this analysis, thus fulfilling one of the major tenants of the scientific process—reproducibility.

Summary

This research design should be sufficient to detect small to medium effect sizes and larger in the estimated 62 hospital sample set. A two-way multivariate ANOVA (MANOVA) algorithm will be used to analyze publicly available hospital performance data from New York and CMS. The two independent variables for this MANOVA test are EHR category (whether an EHR is present or not in each hospital), and the teaching category of the hospital (non-teaching, minor teaching, or major teaching hospital), based on previous research (Navathe et al., 2013). The dependent variables will include: acute myocardial infarction (AMI) mortality risk adjusted rate, heart failure mortality risk adjusted rate, pneumonia mortality risk adjusted rate, AMI total costs, heart failure total costs, pneumonia total costs, AMI length of stay, heart failure length of stay, and pneumonia length of stay consistent with analysis methods from previous research (Carretta et al., 2013; Chin et al., 2014; Dolmatova et al., 2016).

Chapter 4: Findings

The purpose of this quantitative correlational study is to examine the performance differences between teaching and non-teaching hospitals in the post-EHR implementation landscape, specifically looking at possible interaction effects between EHRs and hospital teaching status. This study will also include analyses that may help to confirm or disconfirm past research findings regarding the cost differences between teaching and non-teaching hospitals as well as potential quality and efficiency differences after the implementation of EHRs. This knowledge may help to establish whether EHRs have made a meaningful impact on the cost and efficiency of care (in addition to the quality of care) in teaching hospitals. There will also be an attempt to re-establish the baseline cost differences between teaching and non-teaching hospitals post-EHR, where teaching hospitals are further stratified into minor and major teaching hospitals per guidance from previous research (Navathe et al., 2013).

This chapter is organized first to provide an overview of the data analysis and statistical assumption evaluation procedures used, reporting the results of three two-way MANOVA analyses, followed by the evaluation of results, and then the chapter summary. Each of the hypotheses from Chapter 1 is addressed and evaluated in light of the corresponding MANOVA results. Overall, all 27 research questions (or 54 hypotheses) are summarized in this chapter. Additionally, the evaluation of results section of this chapter provides a brief summary of the significance of the research questions in the context of previously published research. The significance of the findings is also further examined in Chapter 5.

Validity and Reliability of Data

In order to address the validity and reliability of the data collected in this research study, the assumptions of the chosen statistical analysis algorithm must be evaluated in light of the data collected. It has been noted that the results of statistical analysis can prove unreliable or faulty if the statistical assumptions are not met (Field, Miles, & Field, 2012). The chosen statistical analysis algorithm is the two-way multivariate Analysis of Variance (MANOVA). MANOVA has four primary statistical assumptions: (1) independence, (2) random sampling, (3) multivariate normality, and (4) homogeneity of covariance matrices (Field et al., 2012). It is worth noting that since the two independent variables are categorical (each with two levels), no statistical analysis of these variables was necessary. These factor variables formed the basis for the grouping of the hospitals between EHR status and teaching status. Any statistically significant findings in the MANOVA tests were followed up by individual one-way ANOVA testing with only the statistically significant dependent variable included. All analyses were performed in R (version 3.2.3).

One of the first data analysis tasks is to address the question of statistical power in the research design. Though one could make the strong case that the sampling rate in this study, as compared to the total population, was extremely high (roughly 25% of the population sampled), the choice was made to group two of the original three levels in the teaching category independent variable in order to increase statistical power and allow for more even group sizes in the research design. Whereas the initial research design called for a 2x3 research design where the EHR category had two levels and the teaching category had three levels, the final research design and analysis included a 2x2 design.

The three levels of the teaching category were collapsed to two—the Major teaching hospital level and the Non-Teaching or Minor Teaching hospital category. It should be noted that changing the original 2x3 research design to the new 2x2 research design does not change the needed sample size of 72. It was previously mentioned that even though this research does not include the needed 72 hospitals, the large sampling rate (~25% of the population) should be sufficient to detect small significant effect sizes.

As there were nine dependent variables, with three variables covering each of the three areas of focus in the research design (three variables evaluating the quality dimension, three variables evaluating the efficiency dimension, and three variables evaluating the cost dimension), three distinct two-way MANOVA tests were actually performed. The data preparation and evaluation procedures covering each of the three MANOVA tests are outlined below.

MANOVA of Quality Variables

The first MANOVA test performed was the combined mortality risk adjusted rate MANOVA. In this quality dimension MANOVA, AMI mortality risk adjusted rate, heart failure mortality risk adjusted rate, and pneumonia mortality risk adjusted rate dependent variables were evaluated against the statistical assumptions of the MANOVA test. The first step was to evaluate outliers. For AMI mortality risk adjusted rate, there was one outlier that was greater than four standard deviations above the mean; it was removed. For heart failure mortality risk adjusted rate, there were a total of four cases that were either above or close to three standard deviations above the mean; these were also removed. For pneumonia mortality risk adjusted rate, no cases were above three standard deviations above the mean. After addressing the outliers in the data for these dependent variables, all three displayed normal distributions as evaluated by the Shapiro-Wilk test. After the removals, there were a total of 57 hospitals available for analysis.

The independence assumption of the quality MANOVA was evaluated using the Durbin-Watson test and found to be not statistically significant ($p = .1848$), which confirms the assumption of independence.

The random sampling assumption was not directly addressed in this research design as all hospitals in the population (which was the State of New York) had some or all of the dependent variables publicly available. The deciding choice as to which hospital's data were included was dependent upon which hospitals had data available for all nine dependent variables. Those hospitals that did not have a complete data set in 2014 for all nine dependent variables were excluded from the analysis.

Multivariate normality of the quality MANOVA was evaluated using a multivariate version of the Shapiro-Wilk test. For the quality MANOVA, this assumption failed on three of the four MANOVA groups—EHR group ($p = .004694$), No EHR group ($p = .1317$), Major Teaching group ($p = .01855$), Non-Teaching or Minor Teaching group ($p = .03063$). Even though most of these dependent variables failed the multivariate normality test, performing log-transformation of all dependent variables actually made the problem worse (i.e., created a drastically less normal distribution than the non-transformed variables). The displayed Shapiro-Wilk test *p*-values are not generally that far from a normal distribution. Therefore, the MANOVA analysis will continue with these variables due to a lack of a robust two-way MANOVA test.

The final MANOVA assumption evaluated was the homogeneity of covariance matrices. The variance of the risk rates was determined to be similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 2.39 times bigger than the smallest. For heart failure, the largest value is about 1.44 times bigger than the smallest. For pneumonia, the largest is about 1.82 times larger than the smallest value. The generally accepted threshold value is 2.0 to satisfy this assumption (Field et al., 2012).

The covariance of the risk rates was also similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.99. For AMI to pneumonia (or pneumonia to AMI), it is 1.10. For heart failure to pneumonia (or pneumonia to heart failure), it is 1.28. These are below the threshold of 2.0.

The variance of the risk rates was similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 1.32 times bigger than the smallest. For heart failure, the largest value is about 1.14 times bigger than the smallest. For pneumonia, the largest is about 1.30 times larger than the smallest value. These are below the threshold of 2.0.

The covariance of the risk rates was similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.14. For AMI to pneumonia (or pneumonia to AMI), it is 3.36. For heart failure to pneumonia (or pneumonia to heart failure), it is 1.15. These are generally below the threshold of 2.0.

MANOVA of Efficiency Variables

The second MANOVA test performed was the combined lengths of stay MANOVA. In this efficiency dimension MANOVA, AMI length of stay, heart failure length of stay, and pneumonia length of stay dependent variables were evaluated against the statistical assumptions of the MANOVA test. The first step was to evaluate outliers. For AMI length of stay, one case was removed as it was close to three standard deviations above the mean. For heart failure length of stay, one case was removed as it was close to three standard deviations above the mean. For pneumonia length of stay, one case was removed that was beyond three standard deviations above the mean. After addressing the outliers in the data for these dependent variables, all three displayed normal distributions as evaluated by the Shapiro-Wilk test. After the removals, there were a total of 59 hospitals available for analysis.

The independence assumption of the efficiency MANOVA was evaluated using the Durbin-Watson test and found to be not statistically significant ($p = .5301$), which confirms the assumption of independence.

The random sampling assumption was not directly addressed in this research design as all hospitals in the population (which was the State of New York) had some or all of the dependent variables publicly available. The deciding choice as to which hospital's data were included was dependent upon which hospitals had data available for all nine dependent variables. Those hospitals that did not have a complete data set in 2014 for all nine dependent variables were excluded from the analysis.

Multivariate normality of the efficiency MANOVA was evaluated using a multivariate version of the Shapiro-Wilk test. All four groups in the MANOVA passed the multivariate normality test—EHR group ($p = .09123$), No EHR group ($p = .4772$), Major Teaching group ($p = .2001$), Non-Teaching or Minor Teaching group ($p = .2601$).

The final MANOVA assumption evaluated was the homogeneity of covariance matrices. The variance of the lengths of stay was similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 2.43 times bigger than the smallest. For heart failure, the largest value is about 1.07 times bigger than the smallest. For pneumonia, the largest is about 1.32 times larger than the smallest value. These are generally below the threshold of 2.0.

The covariance of the lengths of stay was similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.28. For AMI to pneumonia (or pneumonia to AMI), it is 2.09. For heart failure to pneumonia (or pneumonia to heart failure), it is 1.23. These are close to the threshold of 2.0.

The variance of the lengths of stay was also similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 1.33 times bigger than the smallest. For heart failure, the largest value is about 1.83 times bigger than the smallest. For pneumonia, the largest is about 1.09 times larger than the smallest value. These are below the threshold of 2.0.

The covariance of the lengths of stay was similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.49. For AMI to pneumonia (or pneumonia to AMI), it is 1.77. For heart failure to Pneumonia (or Pneumonia to heart failure), it is 1.72. These are generally below the threshold of 2.0.

MANOVA of Cost Variables

The third MANOVA test performed was the combined costs MANOVA. In this cost dimension MANOVA, AMI costs, heart failure costs, and pneumonia costs dependent variables were evaluated against the statistical assumptions of the MANOVA test. The first step was to evaluate outliers. For AMI costs, three cases were close to or above three standard deviations beyond the mean; they were removed. For heart failure costs, no cases were close to or beyond three standard deviations beyond the mean. For pneumonia costs, three cases were close to or above three standard deviations beyond the mean; those were also removed. After addressing the outliers in the data for these dependent variables, the cost variables were not normally distributed. Since costs are typically right skewed, a log-transformation is a reasonable approach to adjust the normality. After performing a log-transformation of all cost dependent variables, they were normally distributed as evaluated by the Shapiro-Wilk test. Also, after the outliers were removed, there was a total of 56 hospitals available for analysis.

The independence assumption of the cost MANOVA was evaluated using the Durbin-Watson test and found to be not statistically significant (p = .391), which confirms the assumption of independence.

The random sampling assumption was not directly addressed in this research design as all hospitals in the population (which was the State of New York) had some or all of the dependent variables publicly available. The deciding choice as to which hospital's data were included was dependent upon which hospitals had data available for all nine dependent variables. Those hospitals that did not have a complete data set in 2014 for all nine dependent variables were excluded from the analysis.

Multivariate normality of the costs MANOVA was evaluated using a multivariate version of the Shapiro-Wilk test. All four groups in the MANOVA passed the multivariate normality test—EHR group (p = .3203), No EHR group (p = .1825), Major Teaching group (p = .5497), Non-Teaching or Minor Teaching group (p = .3323).

The final MANOVA assumption evaluated was the homogeneity of covariance matrices. The variance of the costs was similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 2.11 times bigger than the smallest. For heart failure, the largest value is about 1.7 times bigger than the smallest. For pneumonia, the largest is about 1.46 times larger than the smallest value. These are generally close to the threshold of 2.0.

The covariance of the costs was also similar between teaching category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.83. For AMI to pneumonia (or pneumonia to AMI), it is 1.68. For heart failure to pneumonia (or pneumonia to heart failure), it is 1.48. These are below the threshold of 2.0.

The variance of the costs was similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI, the largest value is about 1.04 times bigger than the smallest. For heart failure, the largest value is about 1.32 times bigger than the smallest. For pneumonia, the largest is about 1.34 times larger than the smallest value. These are below the threshold of 2.0.

The covariance of the costs was also similar between EHR category groups (as measured by the difference between largest and smallest values in each group). For AMI to heart failure (or heart failure to AMI), it is 1.22. For AMI to pneumonia (or pneumonia to AMI), it is 1.06. For heart failure to pneumonia (or pneumonia to heart failure), it is 1.31. These are below the threshold of 2.0.

Results

The following represents the original research hypotheses outlined in Chapter 1. Each of these is evaluated below in light of the results of the MANOVA analyses.

H1$_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by AMI mortality risk adjusted rate.

H1$_a$. EHRs have a statistically significant effect on hospital mortality as measured by AMI mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was not statistically significant for AMI mortality risk adjusted rate ($F(3, 53) = 3.33$, p = .0735). Therefore, we fail to reject the null hypothesis—no relationship detected.

H2$_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by heart failure mortality risk adjusted rate.

H2$_a$. EHRs have a statistically significant effect on hospital mortality as measured by heart failure mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was not statistically significant for heart failure mortality risk adjusted rate ($F(3, 53) = .897$, p = .3479). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H3_0$. EHRs do not have a statistically significant effect on hospital mortality rate as measured by pneumonia mortality risk adjusted rate.

$H3_a$. EHRs have a statistically significant effect on hospital mortality as measured by pneumonia mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was not statistically significant for pneumonia mortality risk adjusted rate (F(3, 53) = .5902, p = .44575). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H4_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

$H4_a$. EHRs have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed (p = .3956). The MANOVA analysis was not statistically significant AMI length of stay (F(3, 55) = 1.172, p = .2835). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H5_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

$H5_a$. EHRs have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed (p = .3956). The MANOVA analysis was not statistically significant for heart failure length of stay ($F(3, 55) = .120$, $p = .730$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H6_0$. EHRs do not have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

$H6_a$. EHRs have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed ($p = .3956$). The MANOVA analysis was not statistically significant for pneumonia length of stay ($F(3, 55) = .0874$, $p = .7686$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H7_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by AMI total costs.

$H7_a$. EHRs have a statistically significant effect on hospital cost performance as measured by AMI total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed ($p = .3988$). The MANOVA analysis was not statistically significant for AMI log-transformed total costs ($F(3, 52) = .2026$, $p = .6544$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H8_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H8_a$. EHRs have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed (p = .3988). The MANOVA analysis was not statistically significant for heart failure log-transformed total costs (F(3, 52) = .0779, p = .7813). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H9_0$. EHRs do not have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

$H9_a$. EHRs have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed (p = .3988). The MANOVA analysis was not statistically significant for pneumonia log-transformed total costs (F(3, 52) = .001, p = .9748). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H10_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by AMI mortality risk adjusted rate.

$H10_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by AMI mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was not statistically significant for AMI mortality risk adjusted rate (F(3, 53) = .0776, p = .7816). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H11_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by heart failure mortality risk adjusted rate.

$H11_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by heart failure mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was not statistically significant for heart failure mortality risk adjusted rate (F(3, 53) = .0201, p = .8877). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H12_0$. Teaching status does not have a statistically significant effect on hospital mortality rate as measured by pneumonia mortality risk adjusted rate.

$H12_a$. Teaching status does have a statistically significant effect on hospital mortality as measured by pneumonia mortality risk adjusted rate.

After running the initial data exploration and analysis, the combined mortality risk adjusted rates MANOVA residuals were normally distributed (p = .09922). The MANOVA analysis was statistically significant for pneumonia mortality risk adjusted rate (F(3, 53) = 5.17, p = .02703, η^2 = .0936). A second one-way individual ANOVA using only the pneumonia mortality risk adjusted rate dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and confirmed. The mean for major teaching hospitals was 56.47 mortalities per 1,000 patient discharges with a standard deviation of 17.68. The mean for non-teaching or minor teaching hospitals was 43.13 with a standard deviation of 23.86. Therefore, we reject the null hypothesis—a relationship was detected.

H13$_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

H13$_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by AMI length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed (p = .3956). The MANOVA analysis was statistically significant for AMI length of stay (F(3, 55) = 13.68, p < .001, η^2 = .209). A second one-way individual ANOVA using only the AMI length of stay dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and failed on the test of homogeneity of variance. Given that failure, a robust one-way Kruskal-Wallis ANOVA test was used and found to be statistically significant, confirming the MANOVA significance. The mean for major teaching hospitals was 5.04 days and the standard deviation was 1.13 days. The mean for non-teaching or minor teaching hospitals was 3.956 days and the standard deviation was .727 days. Therefore, we reject the null hypothesis—a relationship was detected.

H14$_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

H14$_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by heart failure length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed (p = .3956). The MANOVA analysis was statistically significant for heart failure length of stay (F(3, 55) = 5.87, p < .05, η^2 = .0979). A second one-way individual ANOVA using only the heart failure length of stay dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and confirmed. The mean for major teaching hospitals was 6.06 days with a standard deviation of .892 days. The mean for non-teaching or minor teaching hospitals was 5.46 days with a standard deviation of .86 days. Therefore, we reject the null hypothesis—a relationship was detected.

H15$_0$. Teaching status does not have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

H15$_a$. Teaching status does have a statistically significant effect on hospital efficiency as measured by pneumonia length of stay.

After running the initial data exploration and analysis, the combined lengths of stay MANOVA residuals were normally distributed (p = .3956). The MANOVA analysis was not statistically significant for pneumonia length of stay (F(3, 55) = .435, p = .5121). Therefore, we fail to reject the null hypothesis—no relationship detected.

H16$_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by AMI total costs.

H16$_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by AMI total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed (p = .3988). The MANOVA analysis was statistically significant for AMI log-transformed total costs (F(3, 52) = 17.30, p < .001, η^2 = .248). A second one-way individual ANOVA using only the AMI log-transformed total costs dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and failed on the normality test. Given that, a robust Kruskal-Wallis ANOVA was used and found statistical significance, confirming the MANOVA significance. As this data set was log-transformed due to the normality violation, what is detected was a statistically significant difference between geometric means of the teaching hospital grouping as opposed to the normal arithmetic means. The arithmetic means or natural group means were not statistically evaluated. So as to not cloud the interpretation of this analysis, the arithmetic means and standard deviations of the groups will not be listed in this context. The geometric mean of the major teaching hospital group was 9.349 with a standard deviation of .436. The geometric mean of the non-teaching or minor teaching hospital group was 8.885 with a standard deviation of .300. It is important to note that the units of these log-transformed costs are no longer in dollars. Therefore, we reject the null hypothesis—a relationship was detected.

$H17_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

$H17_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by heart failure total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed (p = .3988). The MANOVA analysis was statistically significant for heart failure log-transformed total costs ($F(3, 52) = 17.325$, $p < .001$, $\eta^2 = .233$). A second one-way individual ANOVA using only the heart failure log-transformed total costs dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and confirmed. As this data set was log-transformed due to the normality violation, what was detected was a statistically significant difference between geometric means of the teaching hospital grouping as opposed to the normal arithmetic means. The arithmetic means or natural group means were not statistically evaluated. So as to not cloud the interpretation of this analysis, the arithmetic means and standard deviations of the groups will not be listed in this context. The geometric mean of the major teaching hospital group was 9.340 with a standard deviation of .412. The geometric mean of the non-teaching or minor teaching hospital group was 8.90 with a standard deviation of .324. It is important to note that the units of these log-transformed costs are no longer in dollars. Therefore, we reject the null hypothesis—a relationship was detected.

H18$_0$. Teaching status does not have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

H18$_a$. Teaching status does have a statistically significant effect on hospital cost performance as measured by pneumonia total costs.

After running the initial data exploration and analysis, the combined log-transformed costs MANOVA residuals were normally distributed (p = .3988). The MANOVA analysis was statistically significant for pneumonia log-transformed total costs (F(3, 52) = 8.51, p < .05, η^2 = .136). A second one-way individual ANOVA using only the pneumonia log-transformed total costs dependent variable was used to determine the effect size. The statistical assumptions of this second one-way ANOVA were evaluated and confirmed. As this data set was log-transformed due to the normality violation, what is detected was a statistically significant difference between geometric means of the teaching hospital grouping as opposed to the normal arithmetic means. The arithmetic means or natural group means were not statistically evaluated. So as to not cloud the interpretation of this analysis, the arithmetic means and standard deviations of the groups will not be listed in this context. The geometric mean of the major teaching hospital group was 9.177 with a standard deviation of .345. The geometric mean of the non-teaching or minor teaching hospital group was 8.912 with a standard deviation of .285. It is important to note that the units of these log-transformed costs are no longer in dollars. Therefore, we reject the null hypothesis—a relationship was detected.

H19$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by AMI mortality risk adjusted rate.

H19$_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by AMI mortality risk adjusted rate.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to AMI mortality risk adjusted rate ($F(3, 53) = 1.86$, $p = .1783$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .09922$). Therefore, we fail to reject the null hypothesis—no relationship detected.

H20$_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by heart failure mortality risk adjusted rate.

H20$_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by heart failure mortality risk adjusted rate.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to heart failure mortality risk adjusted rate ($F(3, 53) = .1315$, $p = .7183$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .09922$). Therefore, we fail to reject the null hypothesis—no relationship was detected.

$H21_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' mortality rate with and without an EHR as measured by pneumonia mortality risk adjusted rate.

$H21_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' mortality with and without an EHR as measured by pneumonia mortality risk adjusted rate.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to pneumonia mortality risk adjusted rate ($F(3, 53) = 1.78$, $p = .18754$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .09922$). Therefore, we fail to reject the null hypothesis—no relationship was detected.

$H22_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by AMI length of stay.

$H22_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by AMI length of stay.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to AMI length of stay ($F(3, 55) = .286$, $p = .5943$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3956$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H23_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by heart failure length of stay.

$H23_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by heart failure length of stay.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to heart failure length of stay ($F(3, 55) = .116$, $p = .7340$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3956$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H24_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by pneumonia length of stay.

$H24_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' efficiency with and without an EHR as measured by pneumonia length of stay.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to pneumonia length of stay ($F(3, 55) = 1.55$, $p = .2172$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3956$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H25_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by AMI total costs.

$H25_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by AMI total costs.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to AMI log-transformed total costs ($F(3, 52) = .788$, $p = .378$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3988$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H26_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by heart failure total costs.

$H26_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by heart failure total costs.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to heart failure log-transformed total costs ($F(3, 53) = .9282$, $p = .3397$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3988$). Therefore, we fail to reject the null hypothesis—no relationship detected.

$H27_0$. There is not a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by pneumonia total costs.

$H27_a$. There is a statistically significant difference between major or minor and non-teaching hospitals' cost performance with and without an EHR as measured by pneumonia total costs.

The two-way MANOVA analysis was not statistically significant for interaction effects between EHR status and teaching status related to pneumonia log-transformed total costs ($F(3, 52) = .0025$, $p = .9605$). The MANOVA residuals were normally distributed based on the Shapiro-Wilk normality test ($p = .3988$). Therefore, we fail to reject the null hypothesis—no relationship detected.

Evaluation of Findings

These findings indicate that EHRs play no statistically significant role on their own in New York State hospitals as they relate to mortality, length of stay, and cost for AMI, heart failure, and pneumonia adult inpatients. These results for the EHR independent variable are surprising given the common assumption that these advanced information systems should reduce mortality, increase quality, and lower costs (Sharma et al., 2016; Yang et al., 2014; Zlabek et al., 2011). On the other hand, it was discussed in

Chapter 2 that EHR adoption effects are nuanced and conflicting in existing literature, so it is not all that surprising to see that there is no statistically significant effect on these hospitals.

The statistically significant teaching hospital effects seem to confirm previous literature that major teaching hospitals generally cost more, and are less efficient as measured by the proxy measure of length of stay (Dolmatova et al., 2016; Lobo et al., 2014; Nandyala et al., 2014; Zafar et al., 2015). For example, AMI costs for major teaching hospitals were higher (*geometric M* = 9.349, *SD* = .436) versus non-teaching or minor teaching (*geometric M* = 8.885, *SD* = .300). Heart failure costs for major teaching hospitals were higher (*geometric M* = 9.340, *SD* = .412) versus non-teaching or minor teaching (*geometric M* = 8.90, *SD* = .324). Pneumonia costs for major teaching hospitals were higher (*geometric M* = 9.177, *SD* = .345) versus non-teaching or minor teaching (*geometric M* = 8.912, *SD* = .285). AMI length of stay was higher for major teaching hospitals (*M* = 5.04 days, *SD* = 1.13 days) versus non-teaching or minor teaching (*M* = 3.956 days, *SD* = .727 days). Heart failure length of stay was also higher for major teaching hospitals (*M* = 6.06 days, *SD* = .892 days) versus non-teaching or minor teaching (*M* = 5.46 days, *SD* = .86 days). Generally, as was explained in Chapter 2, this trend of more expensive and less efficient care at teaching hospitals has been attributed to the nature of the teaching environment in these institutions and their training of new physicians. Additionally, teaching hospitals also tend to receive the sickest patients as teaching hospitals have the most advanced equipment and are experienced in delivering highly complex care.

The results of the analysis for the pneumonia mortality risk adjusted rate highlight an important distinction and a break from the long-held defense that major teaching hospitals receive the sickest patients and, therefore, cost more, are less efficient, and possibly have higher mortality. As was outlined in Chapter 3, the mortality risk adjusted rates are computed to account for the illness level of the patient. So, theoretically, a pneumonia mortality risk adjusted rate value can be compared from one hospital to another regardless of the actual illness level of individual pneumonia patient populations seen at each institution. In the analysis of pneumonia mortality risk adjusted rate, major teaching hospitals had a higher risk adjusted mortality rate (M = 56.47, SD = 17.68) versus non-teaching or minor teaching (M = 43.13, SD = 23.86). The effect size was 9.36%, meaning that about 9% of the variance of the difference in rates is correlated with teaching status of the hospital.

Summary

In sum, six research questions had statistically significant findings. For example, pneumonia mortality risk adjusted rate for major teaching hospitals was higher than non-teaching or minor teaching hospitals. AMI length of stay for major teaching hospitals was higher than non-teaching or minor teaching hospitals. Heart failure length of stay for major teaching hospitals was higher than non-teaching or minor teaching hospitals. AMI costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Heart failure costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Pneumonia costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Additionally, surprisingly, EHRs did not have a statistically significant effect on quality, efficiency, or costs on the hospitals in this study.

Chapter 5: Implications, Recommendations, and Conclusions

Recent U.S. healthcare legislation reform has created large incentives for clinical information system adoption, specifically electronic health records (Lee & Choi, 2016). The HITECH Act provided healthcare organizations with tens of billions of dollars in incentives over the course of a decade to implement and use EHRs meaningfully (Lee & Choi, 2016). Though the U.S. healthcare enterprise is rapidly implementing EHRs and other clinical information systems due to large governmental incentives, the evidence to prove that these systems lower cost and increase clinical quality is conflicting and nuanced (Burke et al., 2016; Sharma et al., 2016; Tall et al., 2015; Yanamadala et al., 2016).

The teaching status of hospitals and its effect on hospital cost and efficiency has been studied over the last several decades (Rosko, 2004; Williams et al., 2007) but there are few recent studies looking at these factors based on data after the recent healthcare reform legislation and corresponding EHR implementations at an organizational level (Chin et al., 2014; Dolmatova et al., 2016; Zafar et al., 2015). The importance of studying the effects of EHRs on organizations in the post-healthcare reform landscape has been identified as an area of needed research (Gholami et al., 2015).

The problem is that the effects of EHR implementations on hospitals have been varied and nuanced and that teaching hospitals have traditionally differed from other hospitals when it comes to their service delivery. This research study was conducted to look at how EHRs may have affected teaching hospitals in ways different than non-teaching hospitals. By examining this potential distinction, healthcare professionals and lawmakers may be able to refine their application of this technology in these organizations, and properly incentivize its use for the benefit of the patient, the hospital, and the nation.

The purpose of this quantitative correlational study was to examine the performance differences between teaching and non-teaching hospitals in the post-EHR implementation landscape, specifically looking at possible interaction effects between EHRs and hospital teaching status. This study also included analyses that may help to confirm or disconfirm past research findings regarding the cost differences between teaching and non-teaching hospitals as well as potential quality and efficiency differences after the implementation of EHRs. This knowledge may help to establish whether EHRs have made a meaningful impact on the cost and efficiency of care (in addition to the quality of care) in teaching hospitals. There was also an attempt to re-establish the baseline cost differences between teaching and non-teaching hospitals post-EHR, where teaching hospitals are further stratified into minor and major teaching hospitals per guidance from previous research (Navathe et al., 2013).

The research method and design for this study incorporated a two-way multivariate ANOVA (MANOVA) design. The two independent variables for this MANOVA test are EHR category (whether an EHR is present or not in each hospital), and the teaching category of the hospital (non-teaching or minor teaching, and major teaching hospital). The dependent variables included were: acute myocardial infarction (AMI) mortality risk adjusted rate, heart failure mortality risk adjusted rate, pneumonia mortality risk adjusted rate, AMI total costs, heart failure total costs, pneumonia total costs, AMI length of stay, heart failure length of stay, and pneumonia length of stay consistent with analysis methods from previous research (Carretta et al., 2013; Chin et al., 2014; Dolmatova et al., 2016).

The results of the 27 research questions showed that six areas had statistically significant findings. For example, pneumonia mortality risk adjusted rate for major teaching hospitals was higher than non-teaching or minor teaching hospitals. AMI length of stay for major teaching hospitals was higher than non-teaching or minor teaching hospitals. Heart failure length of stay for major teaching hospitals was higher than non-teaching or minor teaching hospitals. AMI costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Heart failure costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Pneumonia costs for major teaching hospitals were higher than non-teaching or minor teaching hospitals. Additionally, EHRs did not have a statistically significant effect on quality, efficiency, or costs on the hospitals in this study.

There are several limitations in this study. For example, this data primarily comes from New York State for the risk-adjusted mortality rates for the disease conditions of interest, as well as the inpatient discharge level data for costs and lengths of stay for these disease conditions. Since the data primarily comes from a single state, and that state imposes certain regulations on its healthcare organizations not imposed by other states (e.g., CON constraints), the generalizability of these results may be limited to states with similar regulatory and patient population characteristics.

This chapter is organized around four main sections. The first is the implications section where results are considered against the backdrop of the intent of the research study. The second section is the recommendations for practice where the results of this research study could be used to influence how different types of healthcare organizations use and implement EHRs. The third section is the recommendations for future research where the results of this research study are discussed with an eye toward extending this research.

Implications

As this research study incorporated a rather complicated research design and analyses (several factorial two-way MANOVA tests) where the efficacy of EHRs, teaching status, and possible interaction effects were explored, it is reasonable to group the implications of this research study by themes. This study incorporated 27 research questions, analyzed by three distinct two-way MANOVA tests, which were necessary to thoroughly explore the dimensions of quality, efficiency, and costs between different groupings of hospitals based on EHR status and teaching status as well as detect any possible interaction effects between EHR status and teaching status. The following is a discussion of the implications of this research in light of three main themes: (1) teaching hospital effects on quality, efficiency, and cost of care, (2) EHR effects on quality, efficiency, and cost of care, and (3) an interaction effect between EHR status and whether the hospital is a major teaching hospital or non-teaching or minor teaching hospital.

Teaching Hospital Effects

The first teaching hospital effect found was in the quality dimension of pneumonia mortality risk adjusted rate. There was a statistically significantly higher rate of pneumonia mortality at major teaching hospitals in New York State. The effect size was small (~9.36%) but present. This effect size is interpreted as 9.36% of the variance in pneumonia mortality risk adjusted rate between groups is correlated with teaching status.

This finding is interesting as the rate was already risk adjusted to account for the sickness of the patient—which means a hospital that receives sicker pneumonia patients is not penalized in this calculated rate as compared to hospitals that receive less sick pneumonia patients. There was not a statistically significant finding observed for the other two measurements of quality (AMI mortality risk adjusted rate and heart failure mortality risk adjusted rate) at teaching hospitals. One of the possible explanations for this difference only appearing for pneumonia and not for AMI or heart failure could be the method whereby pneumonia mortalities are recorded at these organizations. For example, do major teaching hospitals more accurately attribute pneumonia mortality as compared to non-teaching or minor teaching hospitals? Do non-teaching or minor teaching hospitals incorrectly attribute legitimate pneumonia mortality to some other disease process? These are possible examples of a type of measurement error possibly introduced by the individual hospitals in New York State.

When investigating the hospital teaching status effect on the quality of healthcare services, the extant literature from the last five years is similarly conflicting. There are studies that show lower quality (Chin et al., 2014), mixed or no effect on quality (Carretta et al., 2013; Fineberg et al., 2013; Nandyala et al., 2014; Navathe et al., 2013; Sandhu et al., 2013; Zafar et al., 2015), and higher quality at teaching hospitals (Bir et al., 2015; Dolmatova et al., 2016; Hansen et al., 2013; Hyder et al., 2013; Lai, Lin, & Du, 2014; Sheetz et al., 2016). Generally, the theme in the recent literature is that teaching status either favors lower mortality or has a mixed effect or no effect on mortality. The findings of this research study demonstrate there is a small correlation between teaching status and higher pneumonia mortality, which is contrary to the majority of recent literature.

The second teaching hospital effect found was in the efficiency dimension of lengths of stay for AMI and heart failure patients. There was a statistically significantly higher length of stay for AMI patients and heart failure patients. There was a medium effect size for AMI patients (~20.9%) and a small effect size for heart failure patients (~9.79%). This effect size is interpreted as 20.9% of the variance in AMI length of stay between groups is correlated with teaching status. Similarly, 9.79% of the variance in heart failure length of stay between groups is correlated with teaching status. As the lengths of stay measurements are not risk adjusted, the commonly cited explanation is that increased lengths of stay in major teaching hospitals are attributed to the sicker patients seen in these organizations.

When investigating the hospital teaching status effect on the efficiency of healthcare services, the extant literature from the last five years is similarly conflicting. There are studies that show lower efficiency (Dolmatova et al., 2016; Lobo et al., 2014; Nandyala et al., 2014), mixed or no effect on efficiency (Fineberg et al., 2013; Lai, Lin, & Du, 2014; Zafar et al., 2015), and higher efficiency at teaching hospitals (Chin et al., 2014; Hyder et al., 2013). Generally, the theme in the recent literature is that teaching status either lowers efficiency or has a mixed effect or no effect on efficiency of hospitals. The findings of this research study demonstrate there is a medium correlation (with AMI) and a small correlation (with heart failure) and lower efficiency at major teaching hospitals, which supports the majority of recent literature.

The third teaching hospital effect found was in the cost dimension for AMI, heart failure, and pneumonia patients. There were statistically significantly higher log-transformed costs for AMI, heart failure, and pneumonia patients. There was a medium effect size for AMI patients (~24.8%), a medium effect size for heart failure patients (~23.3%), and a small effect size for pneumonia patients (~13.6%). This effect size is interpreted as 24.8% of the variance in AMI log-transformed costs between groups is correlated with teaching status. 23.3% of the variance in heart failure log-transformed costs between groups is correlated with teaching status. Similarly, 13.6% of the variance in pneumonia log-transformed costs is correlated with teaching status. As these cost measurements are not risk adjusted, again, the commonly cited explanation is that increased costs in major teaching hospitals are attributed to the sicker patients seen in these organizations.

When investigating the hospital teaching status effect on the cost of healthcare services, the extant literature from the last five years shows that teaching hospitals generally cost more. There are, however, studies that show mixed or no effect on cost (Adrados et al., 2015; Bir et al., 2015; Chin et al., 2014; Fineberg et al., 2013; Nandyala et al., 2014), as well as higher cost at teaching hospitals (Dolmatova et al., 2016; Zafar et al., 2015). No studies were found that definitively showed lower costs at teaching hospitals. The findings of this research study demonstrate there is a medium correlation (with AMI and heart failure) and a small correlation (with pneumonia) and higher costs at major teaching hospitals, which supports the majority of recent literature.

EHR Effects

The extant recent literature surrounding EHR effects on quality, efficiency, and costs of patient care generally show mixed results. For example, EHR use has shown to provide mixed results along the dimension of quality of healthcare service delivery. There are examples where EHR use positively affected (lowered) mortality, reduced hospital readmissions, and reduced medical errors (Ben-Assuli et al., 2013; Gholami et al., 2015; Zlabek et al., 2011). On the other hand, there were examples of mixed quality performance due to EHR use, where there was either no significant difference in performance after EHR adoption or there was an increase in quality in one area while there was a decrease in quality in another area (Lee et al., 2013; Sharma et al., 2016; van Poelgeest et al., 2015).

Along the cost dimension, extant literature shows that EHR use has been found to be associated with mixed results at an industry level. For example, one study has found that EHR adoption has lowered the cost of care (Zlabek et al., 2011). One study found mixed results when it comes to the cost of healthcare service delivery (Sharma et al., 2016). One study found that EHR use, specifically advanced EHR use, increased the cost of care by 7% (Teufel et al., 2012).

Along the efficiency dimension, extant literature shows EHR adoption and use is filled with the most examples of mixed results. For example, there are studies that show the EHR use increases revenue, reduces length of stay, and increases efficiency (Gholami et al., 2015; Lee & Choi, 2016; Lee et al., 2013; Yang et al., 2014; Zlabek et al., 2011). There are also studies that show the EHR adoption and use do not significantly affect organizational performance (Adler-Milstein et al., 2015; Bae & Encinosa, 2016; Henning et al., 2013; Tall et al., 2015). Finally, there are studies that show that EHR adoption and use have had a negative effect on organizational performance, when it comes to productivity and patient throughput (Huerta et al., 2013; Lam et al., 2015).

This research study did not find any statistically significant findings for EHR effects on quality (as measured by AMI, heart failure, and pneumonia risk adjusted rates), costs (as measured by the log-transformed costs of AMI, heart failure, and pneumonia patients), or efficiency (as measured by lengths of stay for AMI, heart failure, and pneumonia patients). This is remarkable given the commonly circulated idea that EHRs can significantly help with patient care in a number of ways. The findings of this research study support the group of literature that demonstrates EHRs have no significant effect on quality, cost of care, and efficiency (as measured by the nine dependent variables of interest) in New York State.

Interaction Effect

There was no extant literature found discussing possible interaction effects of EHR status and teaching status. The findings of this research study demonstrate no statistically significant interaction effect between EHR status and teaching status of hospitals (as measured by the nine dependent variables of interest) in New York State hospitals. The implication appears to be that hospital leadership can approach EHR implementations in their hospitals as distinct projects and do not need to frame those EHR projects in the light of their organizational teaching status. There appears to be no discernable effect between these predictors.

Recommendations for Practice

There are several recommendations for practice that come out of this research. These recommendations will allow those in the healthcare industry to potentially focus their EHR projects, taking into consideration the effects those information systems have on the delivery of care as well as having a fuller understanding of how these systems may or may not interact with their type of hospital. Additionally, it is valuable to understand the differences between types of hospitals when it comes to the quality, cost, and efficiency of healthcare service delivery.

As previously mentioned, one of the most striking outcomes of this research is that EHR status has not been shown to correlate with an increase in quality (as measured by AMI, heart failure, or pneumonia mortality risk adjusted rates), a decrease in costs (as measured by the log-transformed costs of AMI, heart failure, or pneumonia patients), or a decrease in lengths of stay (as measured AMI, heart failure or pneumonia patients). Though the existing literature is relatively conflicting, this research study supports the position that EHRs do not have a significant impact in these areas. Of course, there are many potential explanations for this. For example, just the fact that an organization has implemented and is using an EHR does not mean that organization is using it well or fully. Perhaps the healthcare industry must mature in its processes and workflows in order to fully utilize these complex information systems and, therefore, realize the potential benefits for their patients. On the other hand, it is comforting to see that EHR status does not have a statistically significant negative impact on healthcare service delivery, either. So, the first recommendation for practice for healthcare leaders is to begin to explore and fully utilize EHRs in their internal processes and workflows to potentially see patient care benefits.

It has also been shown in this research study that there is no detectable interaction effect between EHR status and teaching hospital status. In effect, what this means is that hospital leadership should likely approach EHR implementations as separate projects, independent of the type of hospital where it is implemented. For example, if a large health system conglomerate has a dozen hospitals, with a mix of both major teaching hospitals and non-teaching or minor teaching hospitals, that health system can likely treat each hospital EHR implementation in a similar manner, regardless of the teaching status of that particular hospital. This is the second recommendation for practice.

Finally, teaching hospitals were evaluated based on the dimensions of quality, cost, and efficiency of healthcare services. As previously mentioned, major teaching hospitals cost more and their patients stay in the hospital longer. This is commonly known in the healthcare industry and is usually attributed to the sickness of the patients being treated. The one surprising aspect of this research is in the quality dimension for pneumonia patients treated at major teaching hospitals. As was shown, pneumonia mortality risk adjusted rates are higher at major teaching hospitals, but the observed effect size is small. Given that these mortality risk adjusted rates should take into consideration the sickness of patients, major teaching hospitals' rates should be similar to non-teaching or minor teaching hospitals' rates if the actual mortality rates were the same. Since there is a difference, hospital leadership should consider how pneumonia patients are treated at major teaching hospitals. This is the third and final recommendation for practice.

Recommendations for Future Research

There are three recommendations for future research outlined in this section. These recommendations can be applied by researchers to extend this research study and attempt to answer some of the open questions which have been brought to light. For example, possible measurement error in pneumonia mortality risk adjusted rates, possible risk adjusted length of stay and risk adjusted cost comparison measures, and a potential repeated measures research design to investigate EHR effects on hospitals over time.

The first recommendation for future research is to investigate possible measurement error in the pneumonia mortality risk adjusted rate measure. It has been shown in this research study that pneumonia risk adjusted rates are higher at major teaching hospitals. One possible explanation for this higher observed rate is that there is some form of bias in the definition or collection of this measurement in different hospitals. For example, do major teaching hospitals more accurately attribute pneumonia mortality as compared to non-teaching or minor teaching hospitals? Do non-teaching or minor teaching hospitals incorrectly attribute legitimate pneumonia mortality to some other disease process? These are possible examples of a type of measurement error by the individual hospitals in New York State. Future research should attempt to refine or control this measure to determine if this difference in pneumonia mortality actually exists.

The second recommendation for future research is to more thoroughly explore the efficiency proxy measure, length of stay, at major teaching hospitals as well as the cost differences at major teaching hospitals. As previously shown, lengths of stay and costs are greater at major teaching hospitals than at non-teaching or minor teaching hospitals. Historically, this is attributed to the fact that major teaching hospitals receive sicker patients, so the costs will be higher and it will take longer to treat these patients. Future research should attempt to develop a similar risk adjusted length of stay comparison measure as well as a risk adjusted cost measure to explore these differences. Similar to the mortality risk adjusted rate measures used in this research study, future researchers could compare major teaching hospitals to non-teaching or minor teaching hospitals given such measures.

The third and final recommendation for future research is to look longitudinally at EHR use at hospitals over time. Instead of the simplistic EHR attribute group used in this research study, future research could employ a repeated measures research design where the same hospitals are tracked over the course of several years, looking at EHR use and its possible effect on quality, cost, and efficiency. In such a research design, it may be possible to measure the differences in quality, cost, and efficiency of healthcare service delivery over time. Researchers would need to also have some measure of how integrated the EHR has become in the hospital processes and workflows to attribute the changes to EHR use and not to other process improvement or quality improvement initiatives occurring at the hospital.

Conclusions

In sum, this research study confirmed previous research that major teaching hospitals cost more and their patients stay in the hospital longer than non-teaching or minor teaching hospitals. It was also noted that pneumonia risk adjusted mortality is slightly higher at major teaching hospitals, which tends to contradict the majority of other research that mortality is generally lower at major teaching hospitals. The most important finding of this research is that EHRs seem to have no effect on quality, cost, or efficiency (as measured by AMI, heart failure, and pneumonia inpatient adults) in New York State hospitals. This seems to support the notion that EHR use and effects may be nuanced and complex—it may not be as simple as just using an EHR to see clear patient care benefits. EHR benefits could possibly only be realized through extensive use and tight integration into internal workflows and processes. There was also no detected relationship between

EHR status and teaching status of hospitals as related to AMI, heart failure, and pneumonia measures.

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