Walden University

College of Management and Technology

This is to certify that the doctoral study by

Henry Carter

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Cheryl Lentz, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Howard Schechter, Committee Member, Doctor of Business Administration Faculty

Dr. Reginald Taylor, University Reviewer, Doctor of Business Administration Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2016

Abstract

Relationship Between Hospital Performance Measures and 30-Day Readmission Rates

by

Henry M. Carter

MBA, American InterContinental University, 2009

BS, Alabama State University, 1991

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Walden University

October 2016

Abstract

Medical errors occur at the prescription step due to lack adequate knowledge of medications by the physician, failure to adhere to policies and procedures, memory lapses, confusion in nomenclature, and illegible handwriting. Unfortunately, these errors can lead to patient readmission within 30 days of dismissal. Hospital leaders lose 0.25% to 1% of Medicare's annual reimbursement for a patient readmitted within 30 days for the same illness. United States, lawmakers posited the use of health information technology, such as computerized physician order entry scores systems (CPOES), reduced hospital readmission, improved the quality of service, and reduced the cost of healthcare. Grounded in systems theory, the purpose of this correlational study was to examine the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. Archival data were collected from 117 hospitals in the southeastern region of the United States. Using multiple linear regression to analyze the data, the model as a whole did not significantly predict 30-day hospital readmission rate, F (2, 114) = 1.928, p = .150, R^2 = .033. However, medical reconciliation scores provided a slightly higher contribution to the model (β = .173) than CPOES (β = .059. The implications for positive social change included the potential to provide hospital administrators with a better understanding of factors that may relate to 30-day readmission rates. Patients stand to benefit from improved service, decreased cost, and quality of healthcare.

Relationship Between Hospital Performance Measures and 30-Day Readmission Rates

by

Dr. Henry M. Carter

MBA, American InterContinental University, 2009

BS, Alabama State University, 1991

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

Walden University

October 2016

Dedication

I dedicate this doctoral study to the most beneficent and merciful Creator; without Him, nothing is possible. I also would like to thank my family: my wife Sharronda Blackman-Carter for your love and support. I would like to thank my in-laws Robert and Cleo Blackman for your support. To my children, Jontavious Carter, Kenya Carter, Shanice Carter, Myesha Carter, and Saladin Carter, I strive to be an example for you, for you are my legacy. I dedicate this doctoral study to my late mother and father, Bernice Carter and Henry C. Wallace, and to my siblings, Jeffrey Carter, Marilyn Carter, and C. Chandon Carter, and to my aunts Virginia Carter- Bennett, Marian Carter-Baxter, and Willie Lou Carter

Acknowledgments

I would like to thank the doctoral committee for assistance with this study: Chairperson Dr. Cheryl Lentz, Second Committee Chairperson Dr. Howard B. Schechter, URR, Dr. Reginald Taylor, and Dean Dr. Freda Turner. Dr. Lyn Walden, you are an awesome person, and I could not have asked for a more knowledgeable and caring guide. In addition, I would like to acknowledge Dr. Moussa Berete for his support throughout this study and Winston Williams and Diane Baker-King for their friendship. I would like to acknowledge my colleagues at Atlanta Technical College for their words of encouragement.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

The focus of this study was on the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. Hospital leaders lose revenue from Medicare when doctors readmit a patient within 30 days for the same illness (McCormack et al., 2013). The aim of the study was to provide hospital leaders with the insight that may help to reduce 30-day readmission rates and potentially improve the quality of care (Fletcher, 2013). Reducing healthcare cost improves access to healthcare for society (McNair & Luft, 2012).

Background of the Problem

Given the increasing healthcare costs in many countries, researchers and lawmakers focus on reducing hospital readmission as one way to improve patient outcomes and reduce the readmission rate (McHugh, Carthon, & Kang, 2010). Medicare inpatients who return to the hospital within 30 days of discharge account for $17 billion in annual Medicare spending within the United States (Shulan, Gao, & Moore, 2013). In response to this increasing cost, lawmakers in the United States developed financial penalties for hospital administrators with high readmission rates. These financial penalties have a negative impact on profitability (McCormack et al., 2013; McHugh, Berez, & Small, 2013). The Southeastern region of the United States has the highest readmissions rates compared to other regions (Anderson, Golden, Jank, & Wasil, 2012).

Some hospital leaders use tools to promote efficiency and reduce bureaucracy (Shulan et al., 2013). Computerized physician order entry scores and medication reconciliation scores remain factors in determining hospitals' profit margins (P. Lee, Andrade, Mastey, Sun, & Hicks, 2014). Understanding the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission could be an initial step for hospital leadership's consideration for seeking to improve business performance and reduce financial losses.

Problem Statement

Hospitals' readmissions remain a significant performance indicator and source of revenue for hospitals in the United States (Gerhardt et al., 2013). Hospital leaders lose 0.25 to 1% of Medicare's annual reimbursement for a patient readmitted within 30 days for the same illness (McCormack et al., 2013). The general business problem is that U.S. Medicare-eligible hospital leaders experience a loss of profitability when 30-day readmissions occur. The specific business problem is that some hospitals leaders do not know the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. The independent variables included computerized physician order entry scores and medical reconciliation scores. The dependent variable was the 30-day readmission rate. The target population included Medicare-eligible hospitals located in Alabama, Georgia, and Florida. The Southeastern region of the United States has the highest readmissions rates compared to other regions

(Anderson et al., 2012). The implications for positive social change included the potential for the sustainability of Medicare-eligible hospitals.

Nature of the Study

Method

The quantitative method suited the needs for this study because the purpose of this study was to analyze numerical data and to generalize findings to a larger population. The focus of a qualitative researcher is to understand the beliefs, experiences, and perspectives of study participants (Zachariadis, Scott, & Barrett, 2013). Furthermore, qualitative researchers rely on collecting and analyzing non-measurable data (Richardson, Abraham, & Bond, 2012). Therefore, the qualitative method did not suit the needs of this study. Mixed methods researchers collect and analyze both qualitative and quantitative data, which can be complex and time-consuming (Venkatesh, Brown, & Bala, 2013). Therefore, a mixed method did not suit the needs for this study.

Design

Researchers use correlation designs to examine relationships between variables (Sparks & Pan, 2010). A multiple linear regression designs suited the needs of this study because the focus of this study was to examine the relationship between the predictor variables, computerized physician order entry scores and medication reconciliation scores, and the dependent variable, 30-day readmission rates. Researchers recommended designs such as experimental and quasi-experimental designs when the study focus is to assess cause and effect (Handley, Schillinger, & Shiboski, 2011). The focus of this research study was to examine the strengths and direction of any relationships. Therefore, an experimental or quasi-experimental design did not suit the needs of this study, because I did not attempt to influence the variables.

Research Question

What is the relationship (if any) between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates for Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida?

Hypotheses

$H1_0$: There is no statistically significant relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates of Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida.

$H1_a$: There is a statistically significant relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates for Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida.

Theoretical Framework

Systems theory first appeared in the literature in 1936 (Roussel, Swansburg, & Swansburg, 2006). Von Bertalannffy (1972) theorized that general systems theory could be useful for management research. Von Bertalannffy characterized the system by the nonlinear interactions of constituent components and interactions (as cited in Walonick, 1993). Adherents of system theory look at the world as subsystems where each system includes defined boundaries (von Bertalannffy, 1972). General systems theorists and researchers often link systems thinking to the study of change management models (Roussel et al., 2006). The system theoretical framework appears appropriate for this study because of the various segments of the healthcare system (Shaw, 2014). Computerized physician order entry scores and medication reconciliation scores are part of hospital systems. Therefore, the systems theory met the needs of this study as the theoretical framework.

Definition of Terms

Computerized physician order entry scores (CPOES): The provider's use a computer to enter medication orders into a database (Centers for Medicare & Medicaid Services [CMS], 2014).

Medication reconciliation: This concept refers to the process of comparing a patient's medication orders, to all of the medications the patient has been taking (Conklin, Togami, Burnett, Dodd, & Ray, 2014).

Readmission: This concept refers to a patient returning to the hospital for a prior acute care admission within a specified time interval (Goldfield et al., 2008).

Assumptions

Assumptions are factors or principles that researchers accept that exist, but are without verification or evidence, and are out of the researcher's control (Al-Habil, 2011). One assumption of this study was archival records included relevant data, which could have influenced the relationship between the variables (Lam, 2010). In addition, an assumption in quantitative research is that the results of a study using one particular group could apply to other similar groups (Al-Habil, 2011).

Limitations

Limitations refer to the potential weakness of the study (Lam, 2010). The intent of this quantitative correlational study was to examine how two independent variables, which included CPOES and medication reconciliation scores, related to a dependent variable, which was the hospital 30-day readmission rate. Archival data from the Center for Medicare Services were appropriate for this study. Archival data are any data collected prior to the beginning of the research study (C. Jones, 2010). The weaknesses associated with this study were the usage of archival data, which included data that was collected by the standards of the university's IRB (C. Jones, 2010) and data were collected by people who did use current data collection methodologies (Cheng, Goldschmied, Deldin, Hoffmann, & Armitage, 2015). The variables mediated or moderated the relationship between the predictor and dependent variable (Lam, 2010).

Delimitations

Delimitations refer to factors that define the boundary and limit the scope of a given study (Castro, Garcia, Cavazos, & Castro, 2011). The scope of this study encompassed Medicare eligible hospitals in the Southeastern United States. The following states comprise the Southeastern region of the United States: (a) Alabama, (b) Georgia, and (c) Florida (U.S. Census Bureau, 2012). The Southeastern region has the highest readmissions rates compared to other regions (Anderson et al., 2012), which is why I included these states for study. Data reflected the period of January 1, 2013 to December 31, 2013. The results of this study only apply to Medicare eligible hospitals. In addition, the results do not apply to other regions in the United States.

Significance of the Study

The significance of this study is that the findings might give hospital administrators insight potentially to reduce 30-day readmission rates and potentially improve the quality of care. Hospital readmission remains a significant quality measure of hospitals in the United States (Gerhardt et al., 2013). The goal of this study was to gain increased understanding of the potential and critical relationship between CPOES, medication reconciliation scores, and 30-day readmission rates for Medicare-eligible hospitals in Alabama, Georgia, and Florida. This study represents an initial step in considering possible solutions to hospital readmission issues in the United States.

Contribution to Business Practice

Providing hospital leaders with information regarding the relationship between CPOES, medication reconciliation scores, and hospital 30-day readmission rate may improve the hospital's best practices (Bradley et al., 2012). Understanding this relationship could allow hospital leaders to develop plans to improve performance, and reduce financial losses (McNair & Luft, 2012). Medication reconciliation and CPOE scores have the potential to improve patient safety and avoid a number of medication errors (Zhivan & Diana, 2012).

Implications for Social Change

The implications for positive social change include the potential to provide data to hospital administrators and other hospital leaders that can aid hospital leaders to improve service to patients. The implications for positive social change include the potential for hospital administrators and other hospital officials to improve service to patients.

Hospital administrators may be able to reduce the cost of healthcare for Americans (McNair & Luft, 2012). Reduced readmission rates may also improve the quality of healthcare (Fletcher, 2013).

A Review of Professional and Academic Literature

The literature includes research on various aspects of hospital readmissions (Cornett & Latimer, 2011). This literature review includes current and previous studies that surround hospital 30-day readmission, CPOES, and medication reconciliation scores. Topics covered in this literature review include an overview of hospitals and the healthcare industry in the financial performance of hospitals in the United States, 30-day readmission, CPOES, and medication reconciliation scores.

In the process of finding resources for this literature review, I used the Walden University online library and the DeKalb County Public Library in Lithonia, Georgia. Education Source Complete, Business Source Premier, SAGE full-text, and ProQuest central served as search engines in the review. Relevant keywords for this study is as follows: *healthcare, hospitals, readmission, CPOES, computerized physician order entry scores,* and *medication reconciliation scores.* The search included only peer-reviewed articles, dissertations, and seminal books. A filtered search for studies published after 2009 occurred, except for searches on persistence theories. As shown in Table 1, more than 88% of the references for this study included peer-reviewed sources published after 2010. Table 1 also displays a summary of the types of sources used in this review.

Table 1

Summary of Sources Used in the Literature Review

Reference Type	Total	Less than 5 years	Greater than 5 years	%
Peer-Reviewed Journals	89	87	2	87%
Non Peer-Reviewed Journals	4	4	0	
Dissertations	1	1	0	
Books	3	2	0	
Websites	3	3	0	
Total	100	97	3	

Organization of the Review

The first section of this literature review includes an overview of general systems theory, which is the theoretical framework of the study. The second section includes an overview of hospitals and the healthcare industry in the United States. The third section includes the indicators and drivers of hospitals' financial performance. The last three sections cover the three variables used in the study. The review closes with a summary of reviewed professional and academic literature.

Application to the Applied Business Problem

The purpose of this study was to examine the relationship between CPOES, medication reconciliation scores, and 30-day readmission. Reducing hospital 30-day readmission remains a top priority for U.S. policymakers (Gerhardt et al., 2013). Hospital 30-day readmission is an important indicator of healthcare quality and costs in the United

States (Fletcher, 2013). In the 21st century, CMS introduced many initiatives with the aim of reducing the cost and improving the quality of healthcare in the United States (Bradley et al., 2012). A part of these initiatives included tracking and publishing the 30-day readmission rate for Medicare eligible hospitals (Bradley et al., 2012). Policymakers ruled to penalize hospitals with high readmission rates to hold hospitals accountable for their readmission rates (Shulan et al., 2013).

In 2010, the U.S. Congress passed The Affordable Care Act of 2010, which allowed CMS under the Hospital Readmissions Programs to cut payment for hospitals with high readmission rate. The act started in the fiscal year 2013 (Shulan et al., 2013). The initial scope of the program was to focus on three conditions: (a) heart failure, (b) acute myocardial infarction, and (c) pneumonia (Weiss, 2013). The objective was to reduce Medicare payments by up to 1% in 2013 and up to 3% in 2015 for hospitals with readmissions rate higher than the expected risk-adjusted rate (Averill, Goldfield, & Hughes, 2013).

In 2014, 2,225 hospitals among the 3,359 Medicare eligible hospitals in the United States faced $227 million reductions in Medicare payment because of high 30-day readmission (Healthcare Financial Management, 2013). Because of these policies, hospital 30-day readmission remains an important driver of hospitals' financial performance, as well as a key performance indicator (Fletcher, 2013; Gerhardt et al., 2013). Although scholars and practitioners continue to recognize the importance of hospital 30-day readmission, many hospitals leaders continue to struggle to find the best way to reduce their readmission rates (McHugh et al., 2013). The current literature lacks effective models for predicting hospital 30-day readmission (Shulan et al., 2013).

Patients often return to the hospital because of the poor quality of care during the initial hospitalization; therefore, improving care quality could reduce hospital readmissions (Spaulding & Raghu, 2013). The use of CPOES could improve the quality of care, which in turn, could reduce hospital readmission (Fletcher, 2013; Spaulding & Raghu, 2013). CPOES referred to the electronic entry of a medical order by the prescriber (Spaulding & Raghu, 2013). The historical manual entry and processing by physicians were associated with various issues such as (a) lack adequate knowledge of medications by the prescriber; (b) failure to adhere to policies and procedures; (c) memory lapses; (d) confusion in nomenclature; and (e) illegible handwriting (Spaulding & Raghu, 2013). To address these issues, the leaders at Thomas Jefferson University Hospital used their information system capabilities to develop CPOES (Weiss, 2013).). The goal of this 8-year project was to increase efficiency and safety at the hospital (Weiss, 2013). Following the lead by Thomas Jefferson University Hospital, other hospitals in the United States started adopting CPOES (Zhivan & Diana, 2012). The benefits of CPOES include the improvement of the overall hospital productivity (E. Ford, Huerta, Thompson, & Patry, 2011). Despite the potential benefits, various safety, cost, and adoption issues limit the success of CPOES in hospitals (Vartian, Singh, DeBakey, Russo, & Sittig, 2014; Wang & Huang, 2012; Wright et al., 2013).

In addition to CPOES, medical reconciliation represents a relevant driver of care quality and hospital productivity (Laugaland, Aase, & Barach, 2012; Ripley & Vieira, 2013). Medication reconciliation scores refer to the process of creating a patient's current medication list and comparing that list to the patient's previous medications (Ripley & Vieira, 2013). In 2005, the Joint Commission on Healthcare included medication reconciliation scores as a national patient safety goal to address medication errors (Vogenberg & DiLascia, 2013). Because of the various implementation and adoption challenges, the Joint Commission on Healthcare suspended scoring hospitals on medication reconciliation scores between 2009 and 2011. Then in July 2011, the U.S. government lifted the suspension and reintroduced the third national patient safety goal (Vogenberg & DiLascia, 2013). Medication reconciliation scores have the potential to reduce hospital readmission by improving patient safety and avoiding a number of medication errors. These medication errors include (a) drug interaction, (b) drug duplications, and (c) drug omissions (Benson & Snow, 2012; J. Lee, Tollefson, Daly,& Kielb, 2013; Hoisington, 2012; Hume & Tomsik, 2014; Laugaland et al., 2012; Walker, 2012a).

General System Theory

As the boundaries faded between systems, general system theory attracted the attention of scholar and practitioners (Lier & Hardjono, 2011). In 1936, von Bertalannffy (1972) theorized that general system theory could be useful for management research. Von Bertalannffy characterized the system by the nonlinear interactions of constituent components and interactions. Adherents of system theory examine the world as subsystems with each system having defined boundaries (von Bertalannffy, 1972). General systems theorists and researchers often link systems thinking to the study of change management models (Roussel et al., 2006). The systems theoretical framework appeared appropriate for this study, because of the various segments of the healthcare system (Shaw, 2014).

System thinking entails complex linkages and outcomes between organizational activities (von Bertalannffy, 1972). Often, unique and unknown advantage points exist that modulate organizational staff performance and outcomes (Senge, Carstedt, & Porter, 2001). Hieronymi (2013) argued that system thinking is necessary to understand interlinked organizational structures. Computerized physician order entry and medication reconciliation are a part of hospital systems with unknown relationships with Medicare 30-day readmission rates, which indicated that systems theory appeared suitable as a theoretical framework for this study.

Although popular, general system theory has some limitations (Hieronymi, 2013). Users of the concepts of the general system theory suggested many unsolved challenges (Valentinov, 2012). Researchers should use the theory to understand how systems link. In addition, to assess the performance of an organization using general system theory, the researcher should assess the effects of inputs, transformations, outputs, and interrelationships (Valentinov, 2012).

In the 1950s, Dorothy Johnson presented one of the earliest theories of nursing. Johnson based this theory on a general system theory. The theory focuses on nursing practice as an external force to preserve the organization of the patient’s behavior by means of imposing regulatory mechanisms by providing resources while the patient experienced stress (Hieronymi, 2013). Johnson's (1990) theory emphasized the regulated balance between interdependent functional subsystems within a system (Glenister, 2011).

30-Days Readmission

The 30-day readmission rate is the admission of a patient to a hospital within 30 days after discharge (Gerhardt et al., 2013). Readmission might seem to be good news for hospitals. The more patients return to the hospital; the more hospitals gain additional revenues (Bazzoli, Fareed, & Waters, 2014). This situation might not always be true because readmission is not good news for healthcare payers. Some readmissions are out of the control of hospital staff while other readmissions remain avoidable. Healthcare payers might not be happy to pay for avoidable readmission. Avoidable readmissions decrease readmissions in the inpatient setting (Segal, Rollins, Hodges, & Roozeboom, 2014). The 30-day-readmission data collection period was January 1, 2013, to December 31, 2013.

Readmission is a concern for all healthcare stakeholders because high readmission rates represent a poor outcome of the transitions from a hospital bed to the community (Fletcher, 2013). Tracking the number of unplanned readmissions of patients is an important metric for evaluating hospitals' quality of care in the United States. Increasingly, readmission exists as a performance indicator of hospitals in the United States (Mark et al., 2013). An increase in 30-day readmission rate leads to poor health outcomes and high healthcare cost (Freymann Fontenot, 2014). The CMS uses the 30-day readmission rate as the standard benchmarking metric of hospitals in the United States

(Shulan et al., 2013). The CMS considers 30-day readmission rates of 80th percentile or lower as optimal rates (McHugh et al., 2010).

Hospital management works around the 30-day readmission rate by readmitting patients under the classification of observation (Macy et al., 2012). The technical difference has to do with Medicare reimbursement. Patients readmitted within a 30-day period for the same illness cause the hospital to lose 25% to 1% of Medicare reimbursements (McCormack et al., 2013). Consistency in the designation of patients under observation status among hospitals and payers may be necessary to compare quality outcomes and costs, as well as optimize models of pediatric observation care (Macy et al., 2012). Since the 1960s, the U.S. healthcare spending grew from 6% of GDP in 1965 to 17% in 2011 (D. Kessler, 2011). Moreover, researchers project healthcare spending to be 26% in 2035 (Baicker & Goldman, 2011). In 2013, Medicare spending was approximated $2.8 trillion, or $8,915, per person (CMS, 2014). Researchers estimated that approximately $17 billion of the total Medicare spending related to unnecessary readmission (Shulan et al., 2013).

Researchers also estimated that Medicare spending would grow an average rate of 6.8% annually from 2015 to 2021 (Fletcher, 2013). Although the United States has the highest healthcare spending in the world, the healthcare outcome in the United States remains the worst among other industrial countries (Davis, Schoen, & Stremikis, 2010; Morley, Bogasky, Gage, Flood, & Ingber, 2014). The United States reported higher readmission rates in various health conditions in comparison to other developed countries (Joynt & Jha, 2011). Approximately 20% of Medicare inpatients return to the hospital within 30 days of discharge (Shulan et al., 2013). To face this high spending and low outcome, The Patient Protection Affordable Care Act of 2010 developed new incentives to reduce 30-day readmissions (McHugh et al., 2013). Hospitals with high 30-day readmission rates could lose up to 3% of their Medicare reimbursement by 2015 (McCormack et al., 2013). In 2013, approximately two-thirds of American hospitals faced such penalties (Harvath, Hilu, Nemana, & Sairamesh, 2013).

The priority of any healthcare system is to improve the quality and reduce the cost of healthcare, thereby reducing avoidable readmission (McNair & Luft, 2012). Reducing 30-day readmission is a priority of scholars, hospital leaders, healthcare payers, and lawmakers in the United States (Gerhardt et al., 2013). In the 21st century, this issue became the main issue of the national debate about the healthcare quality and the performance of hospitals (McCormack et al., 2013). In 2011, lawmakers estimated that avoidable 30-day admissions remained at 76% (Fletcher, 2013). Hospital leaders vigorously worked to reduce their readmission rates (McHugh et al., 2010). Furthermore, multiple local and nationally based organizations engaged in helping hospitals to reduce their 30-day readmission (Shulan et al., 2013).

Despite the increasing interest of scholars and practitioners on hospital 30-day readmission, evidence on best practices to reduce readmission is limited (McHugh et al., 2013). Several predictive models exist for hospital readmission; however, many of these models perform poorly (Shulan et al., 2013). The results showed that factors, such as communication between patients and healthcare providers, coordination of the after-discharge, and quality of care during initial hospitalization, are significant drivers of 30-

day readmission (Fletcher, 2013). The main reasons for readmission are the lack of coordination and poor care delivery (Ketterer, Draus, McCord, Mossallam, & Hudson, 2014).

In an experimental study conducted at an inner city academic teaching hospital, Ketterer et al. (2014) examined the effect of a discharge process on hospital readmission. The sample consisted of two groups of participants. The first group of participants received an additional education discharge intervention, and the second group, the control group, received a standard discharge process. The intervention included the assignment of a nurse who served as discharge advocate and a clinical pharmacist whose responsibility was to communicate with the patients on the third day of the discharge. The responsibility of the discharge advocate was to coordinate the discharge and an after hospital care plan, which included educating patients about their medications, their medical condition, and to ensure that the patients were aware of all their follow-up doctor appointments. The nurse and a clinical pharmacist identified and addressed all risks of unplanned readmissions for patients in the intervention group. Participants in the control group did not receive any additional education.

The results of Ketterer et al.'s (2014) study indicated that patients in the intervention group had less risk of readmission than did patients in the control group. In a 2014 quasi-experimental study, Warden, Freels, Furuno, and Mackay (2014) confirmed the important role of a pharmacist in reducing 30-day readmissions. Ketterer et al. and Warden et al. showed that the relationship between patients and various parties involved in the care system plays an important role in minimizing 30-day readmission. Although these two studies contributed to the debate of 30-day readmission, their limitations lie in the fact that they focused only on the discharge process.

A significant number of readmission could decrease by ensuring that patients understand their plan of care (O'Leary et al., 2010). In the process of evaluating how well patients understand their plan of care, O'Leary et al. interviewed physicians and hospitalized patients from an urban academic hospital. The sample included 241 patients and 233 physicians. Patient interviews consisted of asking about knowledge of their physician and nurse names, as well of their primary health condition, changes in their medication, their expected hospitalization length, their planned tests and procedures, and their physician consultants. Physicians responded to the same questions during the interview.

The results of O'Leary et al.'s (2010) study indicated that although 32% of patients identified their physicians by name and 60% identified their nurse by name, only 11% knew the role of their physicians. Among the patients, only 25% knew their discharge date (Scott et al., 2012). In addition, 65% of patients did not know their primary medical conditions, 48% ignored their planned tests, 10% did not know their planned procedure, 61% were not aware of changes in their medications, and 52% did not know their physician consultants (O'Leary et al., 2010). Helping patients understand their plan of care will likely improve the quality of care and reduce unplanned readmission (Fletcher, 2013). Although O'Leary et al. demonstrated that patients lacked knowledge of their plan of care and suggested that reducing this lack might reduce unplanned readmission, the results did not show the direct relationship between the understanding plan of care and 30-day readmission.

The main theme of the study is the lack of knowledge patients have about the processes of the hospital. Higher overall patient satisfaction and satisfaction with discharge planning are associated with lower 30-day risk-standardized hospital readmission rates after adjusting for clinical quality (Boulding, Glickman, Manary, Schulman, & Staelin, 2011). This study could have been stronger if O'Leary et al. (2010) addressed how understanding the plan of care could impact hospital 30-day readmission. Understanding the plan of care could provide hospital leaders with an opportunity to address 30-day readmission.

Hospital unitization, which is the separation of bed units, is another significant driver of readmission (Anderson et al., 2012). Using data from 7,800 surgeries performed in 2007, Anderson et al. (2012) investigated the issues of readmission at large academic hospitals in the United States. The results indicated that highly unitized units had higher readmission rates (Fletcher, 2013). Researchers estimated that additional beds used at the time of discharge increased the likelihood of readmissions (Anderson et al., 2012). In general, patients discharged from highly unitized post-operative units returned within 72 hours (Anderson et al., 2012). High readmission represents poor outcomes (Fletcher, 2013). Some hospitals attempted to work around 30-day readmission rates by classifying patients as *observation* status, which would not count the patient as being a readmitted patient (Macy et al., 2012). In an experimental study conducted at an inner city academic hospital, Ketterer et al. (2014) concluded that patients who received support from a discharge advocate had lower readmissions than those who received a standard discharge.

Using data from the MarketScan Multistate Medicaid Claims Database, Mark et al. (2013) examined the predictors of behavioral health patients. Data were from 2004 to 2009. The sample of the study consisted of the hospital with a minimum of 25 readmissions per year. The median readmission rate for behavioral health patients was 11% (Mark et al., 2013). The results indicated increased follow-up with discharged behavioral health patients is likely to decrease the likelihood of readmission. Mark et al.'s results also indicated that the length of the first admission correlates with lower readmission risk. Increasing the length of hospital stay could decrease the risk of readmission for behavioral health patients, which might not be true for another type of patients (J. Ford, Algert, Morris, & Roberts, 2012).

Similarly, DeLia, Jian, Gaboda, and Casalino (2014) showed that post-discharge follow-up could decrease the risk of readmission. Data for the study of DeLia et al. (2014) consisted of Medicare claims data from 2007 to 2008. Participants were patients with an index admission for health conditions including heart failure, acute myocardial infarction, and pneumonia (J. Ford et al., 2012).

J. Ford et al. (2012) investigated changes in the length of postnatal hospital stay by delivery type, hospital type, the concurrent maternal readmission rates, and the reasons for this readmission. J. Ford et al. used data from 597,475 mothers' birth admissions and 19,094 readmissions in the 6-weeks post-birth in New South Wales from 2001 to 2007. The two delivery types used included vaginal delivery and Caesarean. The two types of hospitals were private and public hospitals. The study outcomes were the postnatal length of stay and the readmission rate per 100 deliveries. The results indicated that the length of postnatal stay decreased for both types of birth in both types of hospitals from 2001 to 2007 (J. Ford et al., 2012). In conclusion, decreasing the length of postnatal stay does not increase the risk of readmission (J. Ford et al., 2012).

Friedman, Jiang, Steiner, and Bott (2012) investigated the impact of the type of Medicare plan on hospital 30-day readmission. Friedman et al. used data from the Agency for Healthcare Research and Quality in 2006 for five states. The two types of Medicare plans included Medicare Advantage plans and the standard fee-for-service program. The results indicated patients with Medicare Advantage plans had a lower risk of readmission than did patients with the standard fee-for-service program (Vertrees, Averill, Eisenhandler, Quain, & Switalski, 2013. Patients with Medicare Advantage plans were younger and less ill than were patients with the standard fee-for-service program (Friedman et al., 2012).

The results of the study indicated that patients with the standard fee-for-service program had a lower likelihood of readmission (Friedman et al., 2012). Friedman et al.'s (2012) study provided insight; however, DeLia et al. (2014) failed to explore the reasons why the chances of readmission of these two groups of patients are different. Post-discharge follow-up could decrease the risk of readmission (Boulding et al., 2011).

Many hospitals in the United States adopted care management technologies to reduce readmission; however, these technologies were expensive and ineffective (Vertrees et al., 2013). An effective readmission-prevention technology should be able to

(a) provide an accurate prediction of risk; (b) synthesize and transform data into actionable insight; (c) focus on activities with higher impact; and (d) bridge care and communication within the organization (Harvath et al., 2013). Information technology (IT) includes likelihood to improve performance through many aspects including increased productivity and better customer experience (S. Dewan & Ren, 2011).

The impact of 30-day readmission rates on hospital's financial performance. As part of the Affordable Care Act (ACA), the U.S. Congress directed the Centers for Medicare and Medicaid Services (CMS) to penalize hospitals with worse than expected 30-day readmission rates (Joynt & Jha, 2012). According to a 2009 study by the Center for Medicare Services, nearly 20% of Medicare beneficiaries admitted to a hospital within 30 days after discharge at an annual cost of $17 billion. Causes of avoidable readmissions include hospital-acquired infections and other complications; premature discharge; failure to coordinate and reconcile medications; inadequate communication among hospital personnel, patients, caregivers, and community-based clinicians; and poor planning for care transition (Berenson, Paulus, & Kalman, 2012).

Financial performance is an important metric of any business including hospitals. The ability to grow financially is a key performance factor in hospital managers' efforts to attract well-qualified healthcare professionals and provide a high quality of care (Singh, Wheeler, & Roden, 2012). Profitable hospitals could retain and reinvest their revenue (Dilwali, 2013). Profitable hospitals attract well-qualified healthcare professionals (Kaufman, 2013).

Hospitals are high revenue generators in the United States; however, high revenue might not necessarily be an indicator of high financial performance. American hospitals generate total revenue of $1.068 trillion (Statistics Brain, 2013). Approximately, 92% of this revenue serves to cover operating expenses (Smith, Bradley, Bichescu, & Tremblay, 2013). Not-for-profit hospitals enjoy the tax exemption benefit that for-profit hospitals do not receive. In 2012, not-for-profit hospital received $12.6 billion in tax exemptions (Rubin, Singh, & Jacobson, 2013).

New U.S. government regulations increased the need for hospital leaders to invest in new technologies (Smith et al., 2013). Analysis of data from 567 U.S. hospitals shows that IT had swift and even patient flow, which in turn improved revenues (Kaufman, 2013). Interestingly, the improvement in financial performance is not at the expense of quality, because similar effects of IT and patient flow in improvements in the quality of patient care exist (Devaraj, Ow, & Kohli, 2013).

The use of healthcare IT received a significant enhancement in the United States because of the American Recovery and Reinvestment Act (ARRA) of 2009 (Detmer, 2010). Hospitals in the United States increasingly adopt electronic medical record (EMR) systems because of new federal regulations. The intent of this adoption is to improve the quality of healthcare in the United States; however, hospital leaders are unsure of the potential impact of EMR on their financial performance (Kazley et al., 2011).

Smith et al. (2013) compared the financial performance of a set of hospitals with sophisticated EMR systems to the financial performance of a set of the similar hospital with less sophisticated EMR systems. The goal was to examine the relationship between

IT governance and hospitals' financial performance (Kazley et al., 2011). The results indicated that hospitals with sophisticated EMR systems could be more profitable than those hospitals without these systems (Kazley et al., 2011).

Despite the value of IT, investing in IT assets only does not improve financial performance (Kohli, Devaraj, & Ow, 2012). Business leaders should combine investment in IT with other business capabilities, such as working relationship with senior leaders to drive financial performance (Karahanna & Preston, 2013). In a study involving 81 hospitals in the United States, Karahanna and Preston showed the nature of the relationship between the chief information officer (CIO) and top management team (TMT) was a significant driver of hospitals' strategic alignment and financial performance.

Various metrics exist to measure hospitals' financial performance. The total profit margin is one of the most popular indicators of a hospital's financial performance (Cleverly, Song, & Cleverly, 2012). Total profit margin refers to a hospital's overall profitability per unit of revenue earned (Singh et al., 2012). Another, popular indicator of a hospital's financial performance includes the operating margin (Cleverley et al., 2012). The operating margin measures profitability with respect to operating activities, which include patient care services (Kirby, 2012). A third commonly used indicator of hospital financial performance is a free cash flow, which focuses on a hospital cash inflow and outflow rather than accounting earnings (Cleverley et al., 2012).

Some scholars argued that free cash flow defines financial performance more closely than reported income does because managers can manipulate reported income

(Singh et al., 2012). Thirty-day readmission impacts the financial performance of hospitals (Zhivan & Diana, 2012). Examining the errors in the process of computerized physician order entry and medication reconciliation could possibly provide the hospitals with metrics that will better measure hospitals' financial performance (Kirby, 2012).

Effective revenue cycle management is a significant driver of a hospital's financial performance (Singh et al., 2012). Revenue cycle management is the process of managing payments and revenue generation (Murphy, Rosenman, McPherson, & Friesner, 2011). In a study involving data from 1,397 not-for-profit hospitals in the United States, Singh et al. (2012) examined the relationship between effective revenue cycle management and hospitals' financial performance. The results indicated that an effective revenue cycle management could drive four financial metrics including (a) operating profit margin, (b) total profit margin, (c) free cash flow, and (d) equity capital.

Technology is another important driver of hospitals' financial performance (S. Dewan & Ren 2011; Karahanna & Preston, 2013; Kohli et al., 2012). Business leaders recognize the value of IT not only as an enabler of business strategy,but also as a driver of financial performance (Karahanna & Preston, 2013). Investment in IT will likely drive financial performance through many aspects including increased productivity and better customer experience (S. Dewan & Ren, 2011). Managers realized the value of the IT investment at various levels including (a) operation, (b) process, and (c) market (Yayla & Hu, 2011). Business leaders make a rational decision on IT investment when they can quantify and justify the contribution of IT to firm performance (Kohli et al., 2012).

In a case study involving non-publically traded hospitals in the United States, Kohli et al. (2012) examined the influence of IT on firm financial performance. The results indicated that the IT investment had more statistically significant influence on firm market value measures than on accounting performance measures (S. Dewan & Ren 2011; Karahanna & Preston, 2013; Kohli et al., 2012). Few hospitals could survive without their information systems being a part of patient care (Dos Santos, Zheng, Mookerjee, & Chen, 2012).

The impact of IT on financial performance may be a function of the portfolio of IT applications used, as well as the assimilation and use of IT in the organization (Setia, Setia, Krishnan, & Sambamurthy, 2011). Setia et al. (2011) identified two dimensions of IT assimilations and use including IT applications architecture spread and IT applications architecture longevity. Next, Setia et al. examined how these two dimensions affect hospitals' financial performance. The results indicated that although the two dimensions could drive hospitals' financial performance, IT applications' architecture longevity has a significant influence (Karahanna & Preston, 2013).

Scholars identified the nature of hospitals' relationship with their suppliers as an important driver of hospitals' financial performance (Germain, Davis-Sramek, Lonial, & Raju, 2011). Using survey data from the top executive of 740 hospitals in the Midwestern United States, Germain et al. examined the relationship between relational supplier exchange and hospitals' financial performance. The results showed two types of relationships based on the responsiveness of the hospital (Moussa, 2013). Relational supplier exchange had a positive relationship with financial performance for high responsive hospital and a neutral relationship with a low responsive hospital (Kohli et al., 2012).

Human capital flow is another significant driver of hospitals' financial performance (Reilly, Nyberg, Maltarich, & Weller, 2014). Given the negative effect of employee turnover on firm financial performance, scholars and practitioners pay more attention to various ways of retaining employees (Dong, Mitchell, Lee, Holtom, & Hinkin, 2012). Employee retention became an important performance indicator and financial performance driver for many organizations (Moussa, 2013). Many organizations fail to retain half of their employees for more than 5 years (Bagga, 2013).

The cost of hiring and training a new employee ranges from 25% to 500% of the annual salary of the employee (Ballinger, Craig, Cross, & Gray, 2011). Employee turnover could affect patient ratification, which in turn, could affect the hospital's financial performance (Reilly et al., 2014). Nurses' voluntary turnover has a significant negative effect on patient outcome (Ellenbecker & Cushman, 2012). In addition to turnover, employees' work-life balance has a significant effect on various hospital outcomes including financial outcome (Avgar, Givan, & Liu, 2011).

In addition to all these drivers, hospital readmission rate became an important driver of hospitals' financial performance (Gerhardt et al., 2013). Given the high cost related to hospital readmission, a hospital leader contends with reducing their 30-day readmission. In 2015, hospitals with 30-day readmissions faced penalties including losing up to 3% of their Medicare reimbursement (McCormack et al., 2013). Medicare started in 2010 to withhold reimbursement to hospitals for readmissions occurring within 24 hours of discharge (Allaudeen, Vidyarthi, Maselli, & Auerbach, 2011). These penalties could have a negative impact on a hospital's financial performance. Historically, the only determinant of hospitals' reimbursement was the amount of care they provide (Fletcher, 2013).

Computerized Physician Order Entry Scores (CPOES)

The process of medication use includes a variety of activities involving various health care professionals and various steps, which include prescription, transcription, administration, and monitoring (E. Ford et al., 2011). This process presents various opportunities for medical errors. Often, medical errors happen at the prescription step because of multiple reasons (E. Jones & Furukawa, 2014). Among other issues, these reasons include a lack adequate knowledge of medications by the prescriber, failure to adhere to policies and procedures, memory lapses, confusion in nomenclature, and illegible handwriting (Spaulding & Raghu, 2013). The use of CPOES could decrease errors in medication use (E. Ford et al., 2011).

CPOES refer to the electronic entry of a medical order by the prescriber (Spaulding & Raghu, 2013). With the use of CPOES systems, healthcare professionals can access patient records, and clinical decision supports in real-time (Spaulding & Raghu, 2013). The use of CPOES could improve the quality of care, which is turn, could reduce hospital readmission (Fletcher, 2013; Spaulding & Raghu, 2013). Furthermore, with the rising cost of healthcare cost in the United States, lawmakers believed the use of health IT, such as CPOES systems, could improve the quality and reduce the cost of healthcare (Zhivan & Diana, 2012).

CPOE systems allowed physicians to enter orders directly into a computer rather than handwriting them (Spaulding & Raghu, 2013). By design, CPOE can eliminate illegible handwriting; avoid transcription errors; improve response time, accuracy, and completeness; in addition, CPOE can improve coordination of care (Coustasse et al., 2013). The ordering stage of medications is where most medication errors and preventable ADEs occur (E. Ford et al., 2011). Using data from 1,014 acute care hospitals in the United States, Spaulding, and Raghu (2013) examined the impact of the use of CPOES systems on cost and the quality of medication management process. Data sources for the study included Health Care Information and Management Systems Society Analytics, Computerized Maintenance Management System, and American Hospital Association.

Despite the known benefit of CPOES usage, the adoption of CPOES systems remains a challenge (Catapano, 2012). In 2011, only 21.7% of hospitals implemented CPOES systems successfully (Alfano, 2013). This adoption rate reached 50% in 2013 (Thompson, 2014). According to Catapano (2012), factors, such as governance structures, engaged collaboration on CPOES, and project management skills, are important determinants of COPE adoption. Various hospital characteristics, such as ownership, location, financial performance, and economies of scale, are significant drivers of CPOES adaption (Zhivan & Diana, 2012). Other driving factors of CPOES adoption include reimbursement policies, characteristics of the insurance market, and competition (Zhivan & Diana, 2012). Alfano (2013) added that the first step in improving physician adoption of CPOES was to develop and implement order sets.

A study led by Dr. David Bates, Chief of General Medicine at Boston's Brigham and Women's Hospital, demonstrated that CPOE reduced error rates by 55%, from 10.7 to 4.9 per 1000 patient days (Leung et al., 2012). Researchers conducted a multicenter retrospective cohort study conducted in six community hospitals with 100 to 300 beds in Massachusetts during a 20-month observation period (January 2005 to August 2006) to access the cost of adverse drug events (Hug, Keohane, Seger, Yoon, & Bates, 2012). The researchers estimated that implementation of CPOE systems at all non-rural United States' hospitals could prevent three million adverse drug events each year (Hug et al., 2012).

Each year in hospitals in the United States, serious preventable medication errors occur in 3.8 million inpatient admissions and cost $16.4 billion (Leapfrog, 2012) (see Figure 1). Errors, such as incorrect dosing, mislabeled drug allergies, harmful drug interactions or dispensing problems, are frequent, and the harm they cause can be significant, even resulting in death. Medication errors are also extremely expensive, costing approximately $4,300 per error (Leapfrog, 2014).

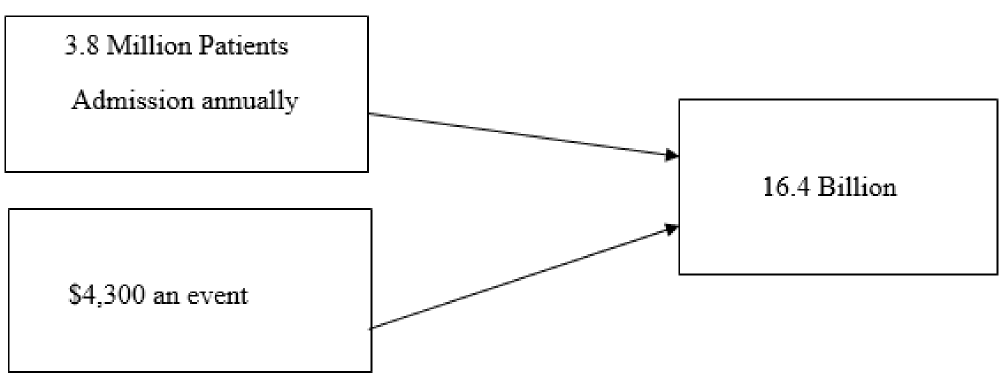

Figure 1. Inpatient preventable adverse drug events

Boston's Brigham and Women's Hospital demonstrated that CPOE reduced error rates by 55% (Hug et al., 2012). A subsequent study showed rates of serious medication errors fell by 88%. The prevention of errors attributed to the CPOE system's structured orders and medication checks (Leung et al., 2012). Another study conducted at Latter Day Saints Hospital demonstrated a 70% reduction in antibiotic-related ADEs after implementation of decision support for these drugs (Leapfrog, 2014).

Medication Reconciliation Scores

On average, every hospitalized patient is a victim of at least one medication error every day (Walker, 2012a). Among all the patient safety errors, medication errors are the most common (Ripley & Vieira, 2013). Medication errors lead to at least one death per day and 1.3 million injuries per year in the United States (Tootelian, Negrete, & Skhal, 2010). Approximately 40% of medication errors are a result of lack of adequate reconciliation (J. Lee et al., 2013). These errors occur at various stages from patient admission to discharge. On average, 22% of avoidable medication errors occur at the admission stage, 66% occur during transfer, and 12% occur at the discharge stage (Conklin et al., 2014).

Furthermore, 20% of medication errors result in harm to patients (J. Lee et al., 2013). Medication errors lead to one out of five injuries or deaths in hospitals (Ripley & Vieira, 2013). Empirical evidence indicated the use of medical reconciliation processes helps to avoid these medication errors (Conklin et al., 2014; Ripley & Vieira, 2013; Walker, 2012a). An effective medication reconciliation score will save medication use by patient and reduce medication errors in the United States (Daly & Lee, 2013).

Medication reconciliation scores referred to the process of creating a patient's current medication list and comparing that list to the patient's previous medications (Ripley & Vieira, 2013). The purpose of medication reconciliation scores is to help avoid a number of medication errors such as drug interaction, duplications, and omissions (Benson & Snow, 2012; J. Lee et al., 2013). Medication reconciliation scores have the potential of reducing hospital readmission (Hoisington, 2012; Walker, 2012b). Medication reconciliation scores improve patient safety and reduce the risk of readmission (Laugaland et al., 2012). Effective medication reconciliation scores and a good patient education strategy remain effective ways of reducing hospitals' readmission rates (Hume & Tomsik, 2014). Taking charge of medication reconciliation scores is the pathway to reducing the readmission rate (Walker, 2012b).

Pharmacists performed medication reconciliation evaluating 20 interventions. The evaluation revealed that in 17 of the 20 interventions, most unintentional discrepancies identified had no clinical significance (Laugaland et al., 2012). Medication reconciliation alone probably does not reduce post discharge hospital utilization, but may do so when bundled with interventions aimed at improving care transitions (Kwan, Lo, Sampson, & Shojania, 2013).

Despite the known benefice of medication reconciliation, hospital leaders struggle to implement medication reconciliation scores processes (A. Lee, Varma, Boro, & Korman, 2014). Maintaining an accurate list of medications in primary care facilities remains challenging (Stewart & Lynch, 2014). A. Lee et al. (2014) argued that reviewing electronic medical records to obtain pharmacist medication histories plays an important role in obtaining an accurate list of a patient's medications. A successful medical reconciliation process should include an interview with patients and use other sources of information including nursing facilities, pharmacies, and physician offices (Sen, Siemianowski, Murphy, & McAllister, 2014).

A meta-analysis of 22 studies focusing on medication history discrepancies found that 10 to 16% of patients had at least one medication history error at hospital admission (Leapfrog, 2014). Many of these medication history errors occur upon admission to or discharge from a clinical unit of the hospital (Ripley & Vieira, 2013). The frequencies of medication reconciliation errors are 20% of ADEs within hospitals. The medication reconciliation process is an effective preventability strategy for the reduction of medication errors and (J. Lee et al., 2013).

Summary

In summary, the literature includes an increasing number of studies on the various issues surrounding hospitals' performance. The 30-day readmission is a significant driver of a hospital's financial performance (Fletcher, 2013). In addition to a significant driver of hospitals' financial performance, the 30-day readmission rate remains an important performance indicator of hospitals in the United States (Gerhardt et al., 2013). Despite the importance of hospitals' 30-day readmission rate, hospital leaders still struggle to find the best way to reduce their readmission rate (McHugh et al., 2013). Many models allow for predicting hospital readmission; however, the majority of these models perform poorly (Shulan et al., 2013).

The purpose of this quantitative correlational study was to examine the relationship between CPOES, medication reconciliation scores, and 30-day readmission rates for hospitals in the states of Alabama, Georgia, and Florida. The lack of a predictive model for hospital 30-day readmission represents an important gap in the literature. In Section 1, I established the foundation for the study. Section 2 includes an expansion about the discussion of the problem statement, purpose, method, and design. Finally, Section 2 includes an explanation of data analysis, data collection, population and sampling, and ethics.

Section 2: The Project

In Section 1, I covered the foundation of the study. Section 2, includes the steps necessary to conduct the study. These steps include the purpose of the study, the role of the researcher, the participants, the research method, and the research design. In addition, this section includes the population and sampling, the ethical research, the data collection, the analysis process, and validity.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between CPOES, medication reconciliation scores, and 30-day readmission rates. The independent variables were CPOES and medical reconciliation scores. The dependent variable was 30-day readmission rates. The target population included Medicare-eligible hospitals located in Alabama, Georgia, and Florida. The Southeastern of the United States has the highest readmissions rates compared to other regions (Anderson et al., 2012). The implications for positive social change included the potential for the sustainability of Medicare-eligible hospitals.

Role of the Researcher

Researchers encounter various ethical and legal challenges in every step of their research (Watts, 2011). An important role of the researcher is to comply with all the applicable legal requirements and codes to conduct a research study (van Deventer, 2009). As a researcher, I abide by all ethical and legal standards of the Belmont report, avoided personal bias, and respected participants' right at every stage of the study. On July 12, 1974, the U.S. Congress signed the National Research Act into law thereby creating the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research (Fiske & Hauser, 2014). The National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research published the Belmont Report to summarize, the basic ethical principles identified by the National Commission in the course of its deliberations (Dahlöf, 2013). In this study, the usage of archival data does not include any personal information or identification of participants. Works of the U.S. government are in the public domain and did not require permission to reuse (CMS, 2014). My intent was to abide strictly by these mandates. No relationship existed with any of the hospitals, and I had no prior association with the topic of this study. In addition, all researchers must receive permission from Walden University's Institutional Review Board (IRB) before collecting data.

Participants

Hospitals in this study included the population of Medicare-eligible hospitals in the Southeastern United States. The southeastern region comprises the states of Alabama, Georgia, and Florida. CMS provides access to data for all Medicare-eligible hospitals (CMS, 2014). Because of the usage of archival data, no direct relationship exists with Medicare-eligible hospitals. This type of study aligns with stratified sampling (Hays & Wood, 2011). Stratified sampling requires accurate information about the population (Belanger et al., 2013).

Research Method and Design

When conducting their studies, researchers have the choice to use quantitative, qualitative, or mixed-method of research (Venkatesh et al., 2013). The nature of this study aligns with the concepts of quantitative research method with a correlational design. This subsection includes the justification of a quantitative method and correlational design as the most appropriate research method and design for this study.

Method

In alignment with the problem and purpose statements, and after consultation with my mentor, the quantitative method was appropriate for this study. Quantitative researchers use measurable data to examine relationships between variables (Rozin, Hormes, Faith, & Wansink, 2012). Quantitative research helps us to understand phenomena by collecting and analyzing numerical data (Griffiths, & Norman, 2013). Quantitative data collection approach can bring breadth to a study by helping researchers gather data about different aspects of a phenomenon from many participants (Venkatesh et al., 2013). Researchers use a qualitative method to understand the beliefs, experiences, and perspectives of study participants (Zachariadis et al., 2013). Furthermore, qualitative researchers rely on collecting and analyzing non-measurable data (Richardson et al., 2012). I used measurable data collected from many participants to determine if there was a relationship between CPOES, medication reconciliation scores, and 30-day readmission rates. Therefore, the quantitative method suited the needs for this study.

Research Design

Correlational researchers focus on the relationship between variables (Sparks & Pan, 2010). The purpose of using correlations in research is to determine the relationship if any, of variables (R. Kessler & Glasgow, 2011). Researchers use correlational design to determine whether an increase or decrease in one variable corresponds to increase or decrease another variable (Ben-Natan et al., 2014). A correlational design suits the needs of the study because the goal of this study was to examine the relationship between the independent variables CPOES, and medication reconciliation scores and a dependent variable, 30-day readmission rates. Researchers recommended designs such as experimental and quasi-experimental designs when the study focus is to assess cause and effect (Handley et al., 2011). The focus of this research study was to examine the relationship, if any, between variables; thus, the experimental and quasi-experimental designs did not suit the needs of the study.

Population and Sampling

The targeted population for this study included Medicare-eligible hospitals in Alabama, Georgia, and Florida. I retrieved data for Medicare-eligible hospitals from the Medicare governmental hospital compare, and hospital safety scores database (CMS, 2014). This type of selection aligns with stratified random sampling. Stratified sampling is a probabilistic sampling method in which the researcher selects participants from a target population based on their fit with the purpose of the study, inclusion, and exclusion criteria (Hays & Wood, 2011). The geographical region for this study was Alabama (20%), Georgia (70%), and Florida (10%) and consisted of Medicare-eligible hospitals (Leapfrog, 2104). Therefore, the sample reflected this geographical stratification demography.

The advantages of using stratified sampling are that the researcher focuses on the priority subpopulations, ignoring the less relevant subpopulations (Goodman, Cryder, & Cheema, 2013). Stratified sampling allows the use of different sampling techniques for different subpopulations. Using this method considerably improves the overall accuracy of the hypotheses and result (Wu, 2013). If population density varies within a region, stratified sampling will ensure accuracy within different parts of the region (Esfahani & Dougherty, 2014).

The first disadvantage of using stratified sampling is the selection of inappropriate stratification variables. The second disadvantage of stratified sampling is the data will not be useful when there are no identical or similar categories or groups (Ye, Wu, Huang, Ng, & Li, 2013). Stratification sampling requires accurate information about the population and is an expensive form of sampling (Belanger et al., 2013).

Researchers use the G*Power 3.1.9 software program to determine the needed sample size for conducting the data analysis (Faul, Erdfelder, Buchner, & Lang, 2009). I conducted a power analysis, using G*Power version 3.1.9 software, to determine the appropriate sample size for the study. An a priori power analysis, assuming a medium effect size (f = .15), a = .05, indicated a minimum sample size of 68 participants was required to achieve a power of .80. Increasing the sample size to 146 would increase power to .99. Therefore, the study consisted of 117. Table 2 indicates the minimum sample size stratification breakdown based upon .80 and .99 power.

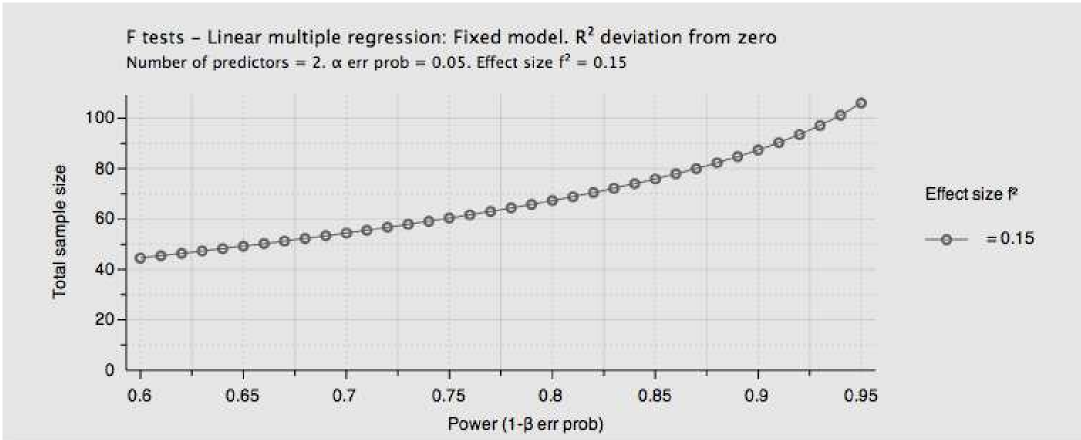

Figure 2. Power as a function of sample size

Table 2

State Stratified Minimum Sample Size at .80 and .99 Power

	Power Level	
State	.80	.99
Alabama	14	29
Georgia	48	102
Florida	6	15
Total	68	146

Non-probability sampling is a sampling technique where the samples do not give all the individuals in the population equal chances of being selected (Callegaro et al., 2014). An advantage of the non-probability method is the tremendous degree of flexibility in setting inclusion probabilities for elements of the sampling frame (Zaman, Rangavajhala, McDonald, & Mahadevan, 2011). When discussing the non-probability method, researchers cannot draw inferences about the larger population (Jiang, Ni, Han, & Tao, 2014).

Ethical Research

Researchers should address ethical challenges at every stage of their studies (Watts, 2011). Walden University requires doctoral students to complete the training for protecting human research participants and obtain approval from the IRB before proceeding to data collection. The proof of completion for protecting human research participants training is located in Appendix A. After applying for and obtaining approval from Walden University's IRB; data collection commenced. In this study, no interaction with the participants occurred. The data collection process did not involve interviews or surveys; therefore, no informed consent was necessary. I stored electronic files in True Crypt and will destroy the hard copies after 5 years.

Data Collection

Data collection in this study did not involve collecting data directly from participants. I did not use any specific data collection instrument to collect data. Archival data exist for the independent variables of CPOES and medication reconciliation scores in the Medicare governmental database of hospitals safety scores. Archival data exist for the dependent variable of 30-day readmission in the U.S. Medicare governmental database of hospital-compare.

In 2011, the Leapfrog group published The Leapfrog Hospital Survey, which assessed hospital performance based on national performance measures. The survey measures a hospital's progress toward implementing a CPOE system and the efficacy of that system in alerting prescribers to common medication errors. These measures are of interest to the patients and hospital administrators. Hospital administrators use these data to determine the progress made in providing quality, improving safety practices, and identifying proficiency of patient care. The Leapfrog Hospital Survey measured the data needed for the independent variables.

Description of the Data

The term CPOE refers to the electronic entry of a medical order by the prescriber (Spaulding & Raghu, 2013). Medication reconciliation scores represent comparing a patient's current medication list to the patient's previous medications list (Ripley & Vieira, 2013). The purpose of medication reconciliation scores is to help avoid a number of medication errors such as drug interaction, duplications, and omissions (Benson & Snow, 2012; J. Lee et al., 2013). The score is a composite made up of 28 different national patient safety measures publicly reported as an A, B, C, D or F letter grade (Leapfrog, 2012)

CPOE. Computerized physician order entry (CPOE) errors occur when the providers use a computer and improperly enters medication orders into the database (CMS, 2014). Computer physician order entry system is a prescription ordering systems that interpret data at the time medications are ordered (Fletcher, 2013; Spaulding & Raghu, 2013). With CPOE, physicians enter orders into a computer rather than on paper. Orders integrated with patient information include laboratory and prescription data, which staff automatically checks for potential errors or problems (Leapfrog, 2014).

Medication reconciliation. Medication errors are common occurrences in hospitals (Leapfrog, 2014). Sometimes these errors happen when patient moves or many people care for him or her. If the entire care team does not know which medications and the dosages the patient received, a medical error could be made, which could cause the patient to suffer (Austin et al., 2014). The most severe medication mistakes might even cause a patient to die. Staff members always check with each other to be sure medical personnel they know which medications and dosage a patient are taken. The hospital staff also uses computerized systems to keep track of a patient's medications (Leapfrog, 2014).

A higher score for the process/structure measures may be because the measures are compliant with best practices in patient care. The Leapfrog Group collected the CPOES scores and medication reconciliation scores with the Leapfrog Hospital Survey (J. Lee et al., 2013). The 30-day readmission rate was also collected by the Leapfrog Group (Leapfrog, 2014).

The Scales of Measurement

The Leapfrog survey measured the two independent variables of CPOE scores and medication reconciliation scores. Both variables reflected the ordinal scale of measurement. Ordinal refers to order in measurement (Cagnone & Monari, 2013). An ordinal scale of measurement allows comparisons of the degree to which two subjects possess the dependent variable (Gadermann, Guhn, & Zumbo, 2012). The statistics used with ordinal are in non-parametric groups (Norman, 2010). Therefore, the ordinal measure suited the needs of this study.

Administration

The Leapfrog Group provided Medicare-eligible hospitals with a voluntarily administered survey (Leapfrog,2014) The hospital CEO/Chief Administrative Officer received an introductory letter requesting the hospital's participation in the survey online during the first week of April 2016. The hospital administrator also received a 16-digit security code to log into the online survey tool. The Leapfrog Hospital Survey is free and open to hospitals from April 1st to December 31st of each year. The annual Leapfrog Hospital Survey assesses hospital safety, quality, and efficiency based on national performance measures (Brooke et al., 2012). These measures and safety practices are of specific interest to health care purchasers and consumers, and cover a broad spectrum of hospital services, processes, and structures (Shahian et al., 2012). These measures also provide hospitals with the opportunity to benchmark the progress they are making in improving the safety, quality, and efficiency of the care they deliver.

Scores and Meaning

The scores for CPOE and medication reconciliation are an ordinal scale of measure ranging along a continuum between 0 and 100 (Leapfrog, 2014). A numerical score is assigned to CPOE for each performance category from the Leapfrog Hospital Survey in the following manner: *fully meets standards* = 100 points, *substantial progress* = 75 points, *some progress* = 50 points, *willing to report* = 25 points (Leapfrog, 2014). For the purposes of this study, the following Likert scale will be used: 3 = *fully meets standards*, 2 = *substantial progress*, 1 = *some progress*. A higher score represents a higher degree of compliance.

A numerical score is assigned to medication reconciliation for each performance category. Hospitals receive either a *fully meets standard, substantial progress, some progress,* or *willing to report* (Austin et al., 2014). Again, a higher score represents a higher degree of compliance. For the purposes of this study, the following Likert-type scale was used: 3 = *fully meets standards*, 2 = *substantial progress*, 1 = *some progress*.

Strategies Use to Address Validity

The strategy used to address the validity of the instrument was construct validity. In 2011, the Leapfrog group invited nine national experts to develop a composite score to evaluate patient safety in hospitals throughout the United States (Leapfrog, 2014). The work involved defining a conceptual framework for the score, assigning a weight to the measure, standardizing scores across measure different types, and identifying methods for dealing with missing data (CMS, 2014). The panel recommended that Leapfrog includes publicly reported measures from national data sources in the score. The panel excluded state reported and regionally reported measures, because of the variations in measures specifications, data collection, and availability that would prevent a consistent comparison across hospitals (Austin et al., 2014).

Process for Completing Hospital Safety Survey

Leapfrog instrument administration focused on measuring and publicly reporting on hospital performance through the annual Leapfrog Hospital Survey (Leapfrog, 2014). The survey is a trusted, transparent, and evidence-based national tool in which more than 1400 hospitals voluntarily participate at no charge. The instrument measures the independent variables and dependent variable and meets the need for this study (CMS, 2014).

Availability of Raw Data

The Center for Medicaid and Medicare services makes raw data available from the hospitals safety score database (CMS, 2014). The public has access to data from the Center for Medicaid and Medicare services without written request. I will retain a copy of the raw data used in this study for 5 years in my password-protected computer and backed up on a password-protected hard drive and will destroy following the retention period.

Data Collection Technique

Data collection is an important aspect of any research study. Inaccurate data collection can affect the results of a study and can ultimately lead to invalid results (University of Wisconsin-Eau Claire, 2014). Data collection in this study included requesting and receiving raw data from the CMS database. The computer physician order entry scores and medication reconciliation scores are archival data with no identifiers collected by The Leapfrog Group from the Leapfrog Hospital Survey (Leapfrog, 2014). The survey measures a hospital’s progress toward implementing a CPOE system and the efficacy of that system in alerting prescribers to common medication errors (Zhang & Shaw, 2012).

Advantages of survey data collection are: (a) numerous questions asked about a topic; (b) advanced statistical techniques utilized to analyze survey data to determine validity, reliability, and statistical significance; and (c) a broad range of data collected

(Jahedi & Méndez, 2014). Disadvantages of survey data collection are (a) closed-ended questions may have a lower validity rate than other question types, (b) question non-responses data errors may exist, and (c) the number of participants who choose to respond to a survey question may be different from those who chose not to respond, thus creating bias (Hertlein, & Ancheta, 2014). The survey method is the preferred method of data gathering for research due to the various advantages, strengths and benefits (University of Wisconsin-Eau Claire, 2014).

The advantages of using archival data are (a) the data already exist, (b) it is less expensive than doing the primary research, and (c) easier access to data (Zhang & Shaw, 2012). The disadvantages of using archival data include less control over the data, and there could be biases in the data (Dikolli et al., 2012). Another disadvantage of archival records includes data, which may influence the relationship between the variables (Lam, 2010). A pilot study was not necessary for this study, because of the use of existing secondary research data.

Data Analysis Technique

Data analysis is a process for obtaining raw data and converting it into information useful for decision-making by users (Linley & Hughes, 2013). Data analysis has multiple facets and approaches, encompassing diverse techniques under a variety of names, in different business, science, and social science domains (Dalal & Zickar, 2012). The focus of data analysis in this study was to seek the answer to the following research question: What is the relationship between CPOES, medication scores, and 30-day readmission rates for Medicare eligible hospitals? I used multiple linear regression to analyze the data.

Multiple linear regression is a statistical technique researchers use when the intent of the study is to predict a quantitative outcome response from more than one predictor variable (Sofowote, Bitzos, & Munoz, 2014). Multiple linear regression is a statistical technique that predicts values of a quantitative dependent variable from values of two or more independent variables (Holmes & Rinaman, 2014). Multiple linear regression remains a mainstay analysis in organizational research (Nimon & Oswald, 2013).

Logistic regression was initially considered. Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables, with varying scales of measurement, by estimating probabilities using a logistic function, which is the cumulative logistic distribution (Liu et al., 2014a). Logistic regression is the probability of the response taking a particular value model based on a combination of values taken by the predictors (Agras et al., 2014). The dependent variable in this study was a scale level of measurement with scale predictor variables. Therefore, logistic regression was not appropriate for this study.

The descriptive statistics include frequencies, percentages, means, and standard deviations (Gravetter & Wallnau, 2008). A difference exists between descriptive statistics and inferential statistics. With descriptive statistics, researchers simply describe what is or what the data show. With inferential statistics, researchers try to reach conclusions that extend beyond the immediate data alone (Rapaport et al., 2014). Descriptive statistics includes observations regarding the distribution of data (Bettis, Gambardella, Helfat, &

Mitchell, 2014). Descriptive statistics also confirm whether hypothesis testing accepts or rejects the null hypotheses (Gravetter & Wallnau, 2008).

Explanation of Data Cleaning and Screening Procedures

The retrieval of archival data from the Centers for Medicare and Medicaid service suits the need of this study. Archival data are any data collected prior to the beginning of the research study (C. Jones, 2010). The secondary analysis of existing data is an increasingly popular method of enhancing the overall efficiency of the health research enterprise (Hui, 2014). Government data normally do not require data cleaning or screening (Wu, 2013).

Explanation for Addressing Missing Data

The Leapfrog Hospital Survey is a voluntary survey. Therefore, many hospitals may choose not to submit a survey (Leapfrog, 2014). The Leapfrog Group disallows scoring of hospitals who did not report on Leapfrog's annual survey (Leapfrog, 2014). Because the missing values are unknown, I could not be 100% certain about the probability of missing data. With a *t*-test for Missing Completely at Random (MCAR), missing data mechanism determined missing data, but it was not very accurate (Doove, Van Buuren, & Dusseldorp, 2014). Many missing data methods assume that MCAR or Missing at Random (MAR) is a better mechanism (Grobler, Matthews, & Molenberghs, 2014). Missing not at Random (NMAR) data mechanism is the probability of a missing value depends on the variable that is missing (Goldstein, Carpenter, & Browne, 2014). NMAR data mechanism is appropriate for addressing missing data in this study. I addressed the missing data by eliminating the data file and selecting another file.

Assumptions Pertaining to the Statistical Analyses

Several assumptions surround the use of multiple linear regression (Loomis, 2014). These assumptions are (a) outliers, (b) multicollinearity, (c) linearity, (d) normality, (e) homoscedasticity, and (f) independence of residuals (Dietz et al., 2014). Researchers must assess these assumptions and identify any statistical corrections utilized to combat these assumptions (Voyer & Voyer, 2015). I will now discuss these assumptions and then identify methods to combat the implication of severe violations of the assumptions.

Outliers. A key assumption is data will not contain any severe outliers (A. Dewan, Corner, & Hashizume, 2014). The implications of an outlier may indicate bad data (Voyer & Voyer, 2015). If the outlying point is, in fact, erroneous, then the researcher should delete the outlying value from the analysis (Loomis, 2014). I assessed the existence of outliers by a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual and scatterplot of the residuals.

Multicollinearity. Multicollinearity is a condition where two predictor variables are highly correlated (Voyer & Voyer, 2015). Multicollinearity can result in misleading and unusual results, inflated standard errors, or reduced power of the regression coefficients that create a need for larger sample sizes (Moran et al., 2014). Multicollinearity was assessed by examining the Pearson Product Moment correlation coefficient between the predictor variables.

Linearity. Linearity defines the dependent variable as a linear function of the predictor (independent) variables (Loomis, 2014). When a violation occurs, all the estimates of the regression including regression coefficients, standard errors, and tests of statistical significance may be biased (Voyer & Voyer, 2015). Violation of this assumption threatens the meaning of the parameters estimated in the analysis (Voyer & Voyer, 2015). I assessed linearity by a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual and scatterplot of the residuals.

Normality. Multiple regression assumes that variables have normal distributions (Loomis, 2014). Various transformations are used to correct non-normally distributed (Hayes & Preacher, 2014). When assumptions are incorrect, multiple regression errors include normal distribution, and a plot of the values of the residuals will approximate a normal curve (Loomis, 2014). I assessed normality by a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual and scatterplot of the residuals.

Homoscedasticity. The assumption of homoscedasticity refers to the equal variance of errors across all levels of the independent variables (Voyer & Voyer, 2015). The assumption can lead to distortion of the findings and weaken the overall analysis and statistical power of the analysis, which results in an increased possibility of Type I error, erratic and untrustworthy *F*-test results, and erroneous conclusions (Voyer & Voyer, 2015). Homoscedasticity can be checked by visual examination of a plot of the standardized residuals by the regression standardized predicted value (A. Dewan et al., 2014). I assessed homoscedasticity by a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual and scatterplot of the residuals.

Independence of residuals. Independence of residuals refers to the assumption that residuals are independent of one another, which implies that subjects are responding independently (Loomis, 2014). When violations of the independence of errors occur, standard scores and significance tests will not be accurate, and there is increased the risk of Type I error (Voyer & Voyer, 2015). One way to diagnose violations of this assumption is through the graphing technique called boxplots in most statistical software programs (Hayes, & Preacher, 2014). The Normal Probability Plot (P-P) of the Regression Standardized Residual and Scatterplot allow access to outliers, normality, linearity, homoscedasticity, and independence of residuals. I assessed the independence of residuals by a visual inspection of the Normal Probability Plot (P-P) of the Regression Standardized Residual and scatterplot of the residuals.

Bootstrapping was conducted to combat the possible influence of any assumptions. Bootstrapping is a statistical technique that allows assigning measures of accuracy to sample estimates (Dovonon, Goncalves, & Meddahi, 2013). Bootstrapping is often used as an alternative to statistical inference based on the assumption of a parametric model when that assumption is in doubt, or where parametric inference is impossible or requires complicated formulas for the calculation of standard errors (Luo, Atamturktur, & Juang, 2012).

Interpretation of Inferential Results

SPSS output yielded various statistics requiring interpretation. Specific parameters to interpret were (a) R^2, (b) *F* value, (c) *B*, (d) *SE B*, (e) *β, t, and sig. (p).* In addition, appropriate bootstrap 95% confidence intervals were reported.

R^2. R^2 is a numerical measure of how much variance in the dependent variable accounts for by the predictor variables (Sowinski et al., 2015). R^2 can range from 0 to 1, where higher values represent more variance (Rahman, 2013). For example, an R^2 value of .17 means the predictor variables account for 17% of the variance in the dependent variable.

F. I used the *F*-ratio of the underlying ANOVA table along with its significance value (Sig. or *p*-value) to determine if the null hypothesis of the research was accepted or rejected (Norris, Plonsky, Ross, & Schoonen, 2015). The *F*-ratio provides the significance of all predictor variables; the associated *p*-value (Sig.), if less than 0.05, confirms the significance of the measure, and could warrant rejection of the null hypothesis (Räz & Sauer, 2015).

B. *B* is an unstandardized coefficient of the predictor variable (Choi, 2015). The negative or positive sign of the *B* value could validate the theory of the model. The value of the *B* value would predict by what factor the value of the dependent variable will change, given a unit change in the predictor variable, given all other predictor variables stayed constant (Räz & Sauer, 2015). The negative or positive sign of the *B* value would validate the theory of the model. The value of the *B* value would predict by what factor the value of the dependent variable will change given a unit change in the predictor variable, given all other predictor variables stayed constant (Räz & Sauer, 2015).

SE B. *SE B* –Standard error for the unstandardized coefficient of the predictor variable shows the degree of noise or irregularity in the data (Kühberger, Fritz, Lermer, & Scherndl, 2015). The standard error of the estimate is the standard deviation of the error term and is the square root of the mean square residual (Von Hippel, 2012).

β. *β* is a standardized coefficient of the predictor variable (Gaskin & Happell, 2014). *β* coefficients represent the amount of change associated with a one-unit change in each of the independent variables (Sowinski et al., 2015). The β is actually the slope of the regression line that mathematically represents the linear regression formula (Räz & Sauer, 2015).

t. The *t*-statistic is a ratio of the departure of an estimated parameter from its notional value and its standard error (Liu et al., 2014b). The *t* statistic is the coefficient divided by its standard error (Yang, Zaitlen, Goddard, Visscher, & Price, 2014). The standard error is an estimate of the standard deviation of the coefficient, the amount it varies across cases (Yin, Zhu, & Kaynak, 2015).

Sig (p). The *P*-value determines how likely it is to get a test statistic (Sullivan, & Feinn, 2012). If the *P*-value is smaller than the significance level α, the outcome will result in a reject the null hypothesis in favor of the alternative (Robinson et al., 2012). If the *P*-value is larger than the significance level α, the outcome will result in a fail to reject the null hypothesis (Li, Yeung, Cherny, & Sham, 2012).

Statistical Software and Version

I used the Statistical Packages for Social Science (SPSS) version 21 as a statistical analysis tool to analyze data in this study. SPSS is a widely used program for statistical analysis in social science. Market researchers, health researchers, survey companies, government, education researchers, marketing organizations, and data miners also use SPSS (Valeri & VanderWeele, 2013). SPSS is the most effective statistical analysis tools used in academic research (Von Hippel, 2012). SPSS Statistics is an integrated family of products that addresses the entire analytical process, from planning to data collection to analysis, reporting, and deployment (Faisel, 2010).

Study Validity

Validity includes definitions regarding how well a test or experiment measures up to its claims (Faisel, 2010). Validity refers to whether the operational definition of a variable reflects the true theoretical meaning of a concept (Linley & Hughes, 2013). The study required an examination of the internal, external, and statistical conclusion threats to validity (Roe & Just, 2009).

Internal Validity

This study was a non-experimental design, and threats to internal validity are not applicable (Avery, Der, Whitsel, & Stürmer, 2014). The purpose of this study was not to evaluate a causal relationship. Therefore, internal validity was not appropriate for this study. I controlled the Type 1 errors by requiring a *p*-value of less than .05 for significance (Faisel, 2010). A *p*-value of less than .05 resulted in the rejecting the null hypothesis for each independent variable (Simonsohn, Nelson, & Simmons, 2014).

External Validity

The Leapfrog group invited nine national experts to develop a composite score to evaluate patient safety in hospitals throughout the United States. The panel recommended Leapfrog include publicly reported measures from national data sources in the score (Leapfrog, 2014). The panel excluded state reported and regionally reported measures because of the variations in measures specifications, data collection, and availability that would prevent a consistent comparison across hospitals (Austin et al., 2014). To improve external validity, researchers should ensure the sample represents the population (Linley & Hughes, 2013).

Statistical Conclusion Validity

Threats to statistical conclusion validity are factors that affect the Type I error rate (Green, Thompson, Levy, & Lo, 2015). The three factors to be discussed are (a) reliability of the instrument, (b) data assumptions, and (c) sample size.

Sample size. A power analysis was conducted to ensure the minimum sample size was identified. A minimum of 68 participants was required. However, I sought between 66 and 146 participants. Raising the number of participants increased the power to .99.

Reliability. The reliability of the instrument determined by running Cronbach's alpha reliability procedure using SPSS. A Cronbach's alpha value of .7 or greater is considered acceptable (De Witte et al., 2013).

I conducted a visual inspection of the normal probability (P-P) plot and a scatterplot of the residuals. Bootstrapping, using 100 samples conducted to combat the possible influence of any assumption violations. Bootstrapping is a statistical technique that falls under the broader heading of resampling and can be used in the estimation of nearly any statistic (Dovonon et al., 2013).

Transition and Summary

The purpose of this quantitative correlational study was to examine the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. Grounded in systems theory, I sought to answer the following research question: What is the relationship (if any) between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates for Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida? The targeted population for this study included Medicare-eligible hospitals in Alabama, Georgia, and Florida. I retrieved data for Medicare-eligible hospitals from the Leapfrog group Medicare governmental hospital compare, and hospital safety scores database (CMS, 2014). Multiple linear regression was the statistical technique that was used to answer the research question. The implications for positive social change included the potential to provide data to hospital administrators and other hospital leaders that can aid hospital leaders to improve service to patients. The implications for positive social change included the potential for hospital administrators and other hospital officials to improve service to patients. Hospital administrators may be able to reduce the cost of healthcare for Americans (McNair & Luft, 2012). Reduced readmission rates may also improve the quality of healthcare (Fletcher, 2013).

In Section 3, I presented and discussed the results of the study. Section 3 includes the following subsections: (a) overview of the study, (b) presentation of the findings, (c) application of the results to professional practice, (d) implications for social change, (e) recommendations for action, (f) recommendation for further research, and (g) summary. Based on the results of the data analysis, I can either reject or accept the null hypotheses and answer the research question.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this quantitative correlational study was to examine the relationship between computerized physician order entry (CPOE) scores, medication reconciliation (MR) scores, and 30-day readmission rates. The final study sample included 117 hospitals. The model as a whole (CPOE and MR) was not a significant model, F (2, 114) = 1.928, p = .150, R^2 = .033, of 30-day hospital readmission rates.

Presentation of Findings

In this section, I will discuss testing of the assumptions, present descriptive statistics, and present inferential statistic results, provide a theoretical conversation pertaining to the findings and conclude with a concise summary. I employed bootstrapping, using 1,000 samples, to address the possible influence of assumption violations. Thus, I presented bootstrapping 95% confidence intervals where appropriate.

Tests of Assumptions

The assumptions I tested were:

1. Multicollinearity
2. Outliers
3. Normality
4. Linearity
5. Homoscedasticity
6. Independence of residuals.

Bootstrapping, using 1,000 samples, enabled combating the possible influence of assumption violations. The evaluation indicated there were some violations of these assumptions. The evaluations of each of these assumptions are as follows:

Multicollinearity. I evaluated multicollinearity by viewing the correlation coefficient between the predictor variables. The Pearson correlation between the predictor variables was .76, indicating the assumption of multicollinearity was not violated.

Outliers, normality, linearity, homoscedasticity, and independence of residuals. Outliers, normality, linearity, homoscedasticity, and independence of residuals were evaluated by examining the Normal Probability Plot (P-P) of the Regression Standardized Residual (see Figure 3) and the scatterplot of the standardized residuals (see Figure 4). The examinations indicated there were some violations of these assumptions. The tendency of the points to lie in a reasonably straight line (see Figure 3), diagonal from the bottom left to the top right, provides supportive evidence there was not a violation of the assumption of normality (Pallant, 2010). However, considerable heteroscedasticity was evident based on the distribution of residuals compared to the predicted values. With that, I computed 1,000 bootstrapping samples to combat any possible influence of assumption violations and reported 95% confidence intervals based on the bootstrap samples where appropriate.

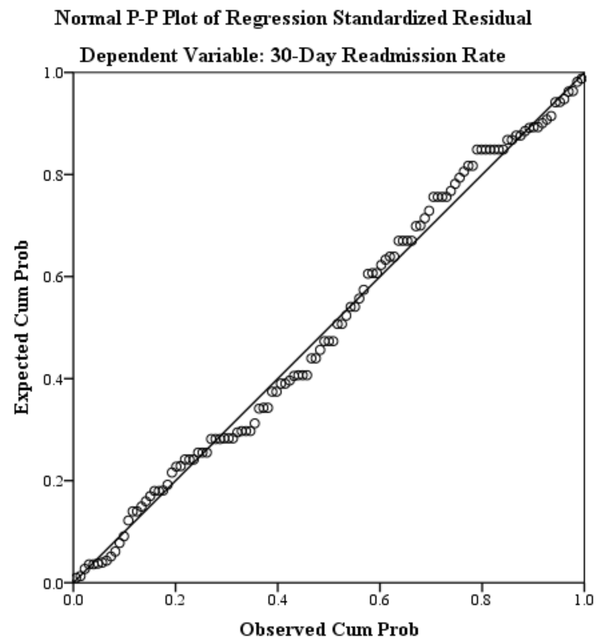

Figure 3. Normal probability plot (P – P) for regression standardized residuals (n = 117)

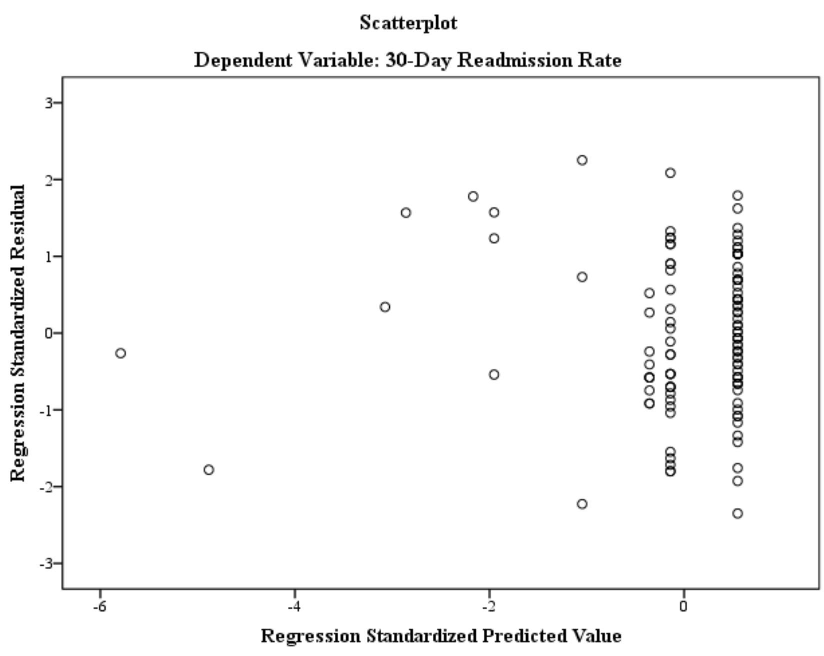

Figure 4. Scatterplot of the standardized residuals (n = 117)

Descriptive Statistics

The data for 412 hospitals from the three study states (Alabama, Florida, and Georgia) initially selected from the database. More than half of the hospitals (55.6%) declined to respond. The three CPOE result categories of interest *fully meet standard* (n = 119), *substantial progress* (n = 50), and *some progress* (n = 4), with *some progress* hospitals dropped from the study because of the small size of that subsample, which made them outliers. Missing data were also a problem for the medical reconciliation and 30-day readmission rate scores, which further reduced the final sample size to n = 117. Almost three-quarters of the hospitals were in Florida (73.5%), and two-thirds of the hospitals (67.5%) fully met the CPOE standard. Table three depicts the mean and standard deviations for the study scale variables. The reason that CPOE results are not in Table 3 with the mean and the standard deviation was that this variable is dichotomous (fully meets standard = 1 versus substantial progress = 0) due to removing *some progress* category as mentioned above. CPOE results indicate 79 hospitals fully meet standards and 38 hospitals meet substantial progress. Table 4 depicts the required versus actual sample size based on state stratification.

Table 3

Mean (M) Standard Deviation (SD) for Study Variables

Variable	*M*	*M* Bootstrap 95% CI	*SD*	*SD* Bootstrap 95% CI
Medical reconciliation	34.16	[33.67, 34.55]	2.46	[1.30, 3.47]
30 Day readmission Rate	17.96	[17.27, 18.18]	1.19	[1.04, 1.31]

Table 4

Required vs. Actual Stratified Minimum Sample Size at .80

State	Required *n*	Actual *n*
Alabama	14	5
Georgia	48	86
Florida	6	26
Total	68	117

Inferential Results

I used standard multiple linear regression, $\alpha = .05$ (two-tailed) to examine the relationship between computerized physician order entry scores, medical reconciliation scores, and hospital 30-day readmission rate. The independent variables were the computerized physician order entry score and the medication reconciliation score. The dependent variable was the hospital 30-day readmission rate. The null hypothesis indicated there was no statistically significant relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates among Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida. The alternative hypothesis was that there was a statistically significant relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates among Medicare-eligible hospitals in the states of Alabama, Georgia, and Florida. I conducted preliminary analyses to assess whether the assumptions of multicollinearity, outliers, normality, linearity, homoscedasticity and independence of residuals were met; I noted some violations for heteroscedasticity.

The model as a whole was not able to significantly predict 30-day hospital readmission rate, $F(2, 114) = 1.928$, $p = .150$, $R^2 = .033$. The R^2 value (.033) indicated that approximately 3% of variations in the 30-day readmission rate accounted for the variation in the dependent variable. Table 5 depicts the regression summary for variables predicting 30-day readmission rate.

Table 5

Regression Analysis Summary for Variables Predicting 30-Day Readmission Rate (n = 117)

Variable	*B*	*SE B*	β	*t*	*p*	*B* 95% Bootstrap CI
Intercept	14.701	2.318		6.343	.001	[11.066, 20.675]
Computerized Physician Order Entry Scores [a]	.149	.262	.059	0.570	.542	[-.369, .669]
Medication Reconciliation	.084	.064	.173	1.315	.123	[-.083, .182]

[a] Entry Scores: 0 = *Substantial Progress* 1 = *Fully Meets Standard*.

Full Model: $F(2, 114) = 1.928$, $p = .15$. $R^2 = .033$.

Analysis Summary

The purpose of this study was to examine the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. A standard multiple linear regression model was used (see Table 5). Assumptions of normality and homoscedasticity were violated; so bootstrapping was employed to provide bootstrapping 95% confidence intervals. The model as a whole was not able to significantly predict 30-day hospital readmission rate, $F(2, 114) = 1.928$, $p = .150$, $R^2 = .033$.

Theoretical Conversation on Findings

Computerized physician order entry and medication reconciliation are a part of hospital systems with unknown relationships with Medicare 30-day readmission rates, which indicated that systems theory appeared suitable as a theoretical framework for this study (Lier & Hardjono, 2011). In 1936, von Bertalannffy (1972) theorized that general systems theory could be useful for management research. Von Bertalannffy characterized the system by the nonlinear interactions of constituent components and interaction (von Bertalannffy, 1972). The results indicated the model, consisting of CPOE and medical reconciliation scores, was not a significant predictor of 30-day readmission rates.

However, others (Ketterer et al. 2010) compared two discharge systems, one comprised of a nurse discharged advocate components and pharmacist component and a second system comprised of the standard discharge process. The former system served as an intervention in an experimental comparison of a control group who participated in the standard discharge system. Ketterer et al. found patients in the experimental discharge system had less risk of readmission than the patients in the control group. Therefore, unlike the findings of this study, Ketterer et al., identified factors influencing the 30 day readmission rate. Likewise, Fletcher (2013) showed that factors, such as communication between patients and healthcare providers, coordination of the after-discharge, and quality of care during initial hospitalization, are significant drivers of 30-day readmission (Fletcher, 2013). Again, these researchers were able to find significant results, unlike the findings of this study. The general systems theory, as applied to this study, did not provide a useful predictive explanation for the 30 day readmission rate.

Applications to Professional Practice

In this paper, the topic discussed included providing hospital administrators with information on CPOES, medication reconciliation scores, and 30-day readmission. Contrary to expectations, I did not find a significant predictor model. Therefore, the results may offer limited applications to professional practice. I have extended the conversation on the topic of 30-day readmission rates and suggest hospital administrators review the study, specifically the literature review, to get a better understanding of the scholarly conversation on the broader topic of 30-day readmission rates. By reviewing literature on the topic, hospital administrators might be able to suggest and invest in future research topics (see Recommendations for Future Research). In addition, hospital administrators must be cognizant of the fact the findings in this study are reflective of a very specific geographic region, and therefore, the results should not be generalized outside this geographical region. However, hospital administrators can use the information to gain great knowledge on the topic of 30-day readmission rates.

Implications for Social Change

The implications for positive social change include the potential to provide hospital administrators with a better understanding of factors that relate to 30-day readmission rates. The potential exists to provide hospital administrators with the necessary tools to reduce 30-day readmission rates through prediction of CPOE and medication reconciliation. The social change implications include the potential for hospital administrators and other hospital officials to improve service to patients.

Society may benefit as hospital administrators develop plans to improve service, reduce financial losses, improve patient safety and avoid a number of medication errors (Zhivan & Diana, 2012). Hospital administrators may be able to reduce the cost of healthcare for Americans (McNair & Luft, 2012).

Recommendations for Action

Based on the results of this study, I am recommending the following. First, hospital administrators should conduct both internal and external surveys. The survey results may help connect hospital performance measures with 30-day readmission rate. Administrators and personnel within hospitals prime objective are to provide impeccable service to patients and should work with them to improve services. Internal surveying could help shape the climate and effectiveness of the working environment.

Second, the data collection must be a priority for administrators and physician in the health industry. Top-ranked hospitals prefer medical professionals who are knowledgeable about preventative measures that could reduce the cost of providing service. Developing agreements between administrators and medical professionals to participate in gathering and sharing data could establish practices for improved services.

Finally, hospital administrators must recognize that ongoing continuing education is necessary to address performance measures that negatively affect 30-day readmission rate Hospital administrators should work toward new strategies to address the challenges of 30-day readmission rates. Hospital administrators should disseminate these strategies to patients, other hospitals, businesses, and governmental agencies via literature, conferences, and training. I will share the results of the study with educational institutions, at medical conferences and by publishing in peer-reviewed journals.

Recommendations for Further Research

I offer the following recommendations for further research. First, future researchers should conduct a quantitative study using a multilevel modeling. Often, there are multiple units of analysis, and data is collected at multiple levels. Such data has a hierarchical structure within individual data (e.g. 30-day readmission rates) nested within larger levels of data (e.g. state). Hierarchical linear modeling is used with nested data to combat for the influence of systematic differences (Raudenbush & Bryk, 2002). For example, there may be systematic differences between the three states, which may account for variations in the 30-day readmission rates. In organizational studies, researchers use multilevel modeling to investigate the influence of factors on an outcome variable when nested data is evident (Raudenbush & Bryk, 2002).

Second, there may be other variables, which are correlates of the 30-day readmission rates, and controlling for the influence of these variables might be beneficial in identifying the efficacy of the CPOE and medical reconciliation scores in 30 predicting-day reconciliation rates. Therefore, researchers should conduct studies where hierarchical linear regression statistical analyses are used to control for the influence of covariates found to be moderately correlated with the 30-day readmission rates.

Third, future researchers can extend the external validity of research findings on correlates of 30-day readmission rates by extending the targeted population to a broader geographical location. In conjunction with cluster sampling, researchers should be able to generalize results to a broader population, due to the importance of readmission to patient health and business profitability.

Fourth, researchers should conduct future research to enhance the internal validity of causes of 30-day readmission rates. Therefore, well-designed randomized control trials should be incorporated. For example, Ketterer et al. (2010) compared two discharge systems, one comprised of a nurse discharged advocate components and pharmacist component and a second system comprised of the standard discharge process and found patients in the experimental discharge system had less risk of readmission than the patients in the control group. Further studies to assess cause and effect are strongly encouraged.

Finally, the results of the study do not apply to other regions in the United States. This study is an initial research study, and more research is needed for examining different ways to reduce 30-day readmission rates. After analyzing the results of this study, I suggest that future researchers address larger geographical areas and gather archival data on hospitals that are mandated by the federal government to report their performance measures.

Reflections

Research is a meticulous journey, and the results of the study close one door and open another door for additional knowledge. Every course was a pathway to learning and developing the skills necessary to completing the study. Upon beginning the research for this doctoral study, it appeared there was a relationship between the independent variables and the dependent variable. The model as a whole was not able to significantly predict 30-day hospital readmission rate. Through their guidance and direction, the committee members and my cohorts made a significant contribution to the scholarly conversation on hospital 30-day readmission rates, CPOE, and medication reconciliation.

Summary and Study Conclusions

Hospitals' readmissions remain a significant performance indicator and source of revenue for hospitals in the United States (Gerhardt et al., 2013). The purpose of this quantitative correlation study, grounded in systems theory, was to examine the relationship, using multiple linear regression, between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates. Data was collected from 117 hospitals located in Alabama, Florida, and Georgia. The model as a whole did not predict 30-day reconciliation rates. Hospitals may apply the use results of this study to add to the body of knowledge and improve professional practices concerning the relationship among CPOES, medication reconciliation scores, and 30-day readmission. Society may benefit as hospital administrators develop strategies to improve service, reduce financial losses and avoid a number of medication errors (Zhivan & Diana, 2012). I recommend that future research gathers data from hospitals in other geographical areas and examine data from hospitals that are mandated by the federal government to report their performance measures. When I started this journey, I was certain I had the answers to conducting a successful study. As I reflect on the last 5 years, I can say it has been a journey that has exposed my strengths and weaknesses. I have learned that to conduct a scholarly study, you must not let your biases influence the outcome.

References

Agras, W. S., Crow, S. J., Halmi, K. A., Mitchell, J. E., Wilson, G. T., & Kraemer, H. C. (2014). Outcome predictors for the cognitive behavior treatment of bulimia nervosa: Data from a multisite study. *American Journal of Psychiatry, 157*, 8-13. doi:10.1176/appi.ajp.157.8.1302

Alfano, S. (2013). Enhancing physician adoption of CPOES: The search for a perfect order set. *Physician Executive, 39*, 30-35. Retrieved from http://www.acpe.org/publications/pej.aspx

Al-Habil, W. (2011). Positivist and phenomenological research in American public administration. *International Journal of Public Administration, 34,* 946-953. doi:10.1080/01900692.2011.615554

Allaudeen, N., Vidyarthi, A., Maselli, J., & Auerbach, A. (2011). Redefining readmission risk factors for general medicine patients. *Journal of Hospital Medicine*, *6*, 54-60. doi:10.1002/jhm.805

Anderson, D., Golden, B., Jank, W., & Wasil, E. (2012). The impact of hospital utilization on patient readmission rate. *Health Care Management Science*, *15*, 29-36. doi:10.1007/s10729-011-9178-3

Austin, J. M., D'Andrea, G., Birkmeyer, J. D., Leape, L. L., Milstein, A., Pronovost, P. J., & Wachter, R. M. (2014). Safety in numbers: The development of Leapfrog's composite patient safety scores for US Hospitals. *Journal of Patient Safety, 10*, 64-71. Retrieved from http://journals.lww.com/journalpatientsafety

Averill, R. F., Goldfield, N., & Hughes, J. S. (2013). Medicare payment penalties for unrelated readmissions require a second look. *Healthcare Financial Management*, *68*(5), 96-98. Retrieved from http://www.hfma.org/

Avery, C. L., Der, J. S., Whitsel, E. A., & Stürmer, T. (2014). Comparison of study designs used to detect and characterize pharmacogenomic interactions in non-experimental studies: a simulation study. *Pharmacogenetics and Genomics, 24*, 146-150. doi:10.1097/FPC.0000000000000027.

Avgar, A. C., Givan, R., & Liu, M. (2011). A balancing act: Work-life balance and multiple stakeholder outcomes in hospitals. *British Journal of Industrial Relations*, *49*, 717-741. doi:10.1111/j.1467-8543.2010.00839.x

Bagga, G. (2013). How to keep the talent you have. *Human Resource Management International Digest*, *21*, 3-4. doi:10.1108/09670731311296401

Bartholomew, D. J. (2013). *Missing data in unobserved variables*. Berlin, Germany: Springer.

Baicker, K., & Goldman, D. (2011). Patient cost-sharing and healthcare spending growth. *Journal of Economic Perspectives*, *25*, 47-68. doi:10.1257/jep.25.2.47

Ballinger, G., Craig, E., Cross, R., & Gray, P. (2011). A stitch in time saves nine: Leveraging networks to reduce the costs of turnover. *California Management Review*, *53*, 111-133. Retrieved from http://cmr.berkeley.edu

Bazzoli, G. J., Fareed, N., & Waters, T. M. (2014). Hospital financial performance in the recent recession and implications for institutions that remains financially weak. *Health Affairs, 33*, 739-745. Retrieved from http://content.healthaffairs.org

Belanger, K., Buka, S., Cherry, D. C., Dudley, D. J., Elliott, M. R., Hale, D. E., & Bracken, M. B. (2013). Implementing provider-based sampling for the national children's study: opportunities and challenges. *Pediatric and Perinatal Epidemiology, 27*, 20-26. doi:10.1111/ppe.12005

Ben-Natan, M., Sharon, I., Barbashov, P., Minasyan, Y., Hanukayev, I., Kajdan, D., & Klein-Kremer, A. (2014). Risk factors for child abuse: Quantitative correlational design. *Journal of Pediatric Nursing*, *29*, 220-227. doi:10.1016/j.pedn.2013.10.009

Benson, J. M., & Snow, G. (2012). The impact of medication reconciliation scores on medication error rates in community hospital cardiac care units. *Hospital Pharmacy*, *47*, 927-932. doi:10.1310/hpj4712-927

Berenson, R. A., Paulus, R. A., & Kalman, N. S. (2012). Medicare's readmissions reduction program a positive alternative. *New England Journal of Medicine, 366*, 1364-1366. doi:10.1056/NEJMp1201268

Bettis, R., Gambardella, A., Helfat, C., & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal*, *35*, 949-953. doi:10.1002/smj.2278

Boulding, W., Glickman, S. W., Manary, M. P., Schulman, K. A., & Staelin, R. (2011). Relationship between patient satisfaction with inpatient care and hospital readmission within 30 days. *The American Journal of Managed Care*, *17*(1), 41-48. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/21348567

Bradley, E. H., Curry, L., Horwitz, L. I., Sipsma, H., Thompson, J. W., Elma, M., & Krumholz, H. M. (2012). Contemporary evidence about hospital strategies for reducing 30-day readmissions. *Journal of the American College of Cardiology, 60*, 607–614. doi:10.1016/j.jacc.2012.03.067

Brooke, B. S., Dominici, F., Pronovost, P. J., Makary, M. A., Schneider, E., & Pawlik, T. M. (2012). Variations in surgical outcomes associated with hospital compliance with safety practices. *Surgery*, *151*, 651-659. Retrieved from http://dx.doi.org/10.1016/j.surg.2011.12.001

Cagnone, S. & Monari, P. (2013). Latent variable models for ordinal data by using the adaptive quadrature approximation. *Computational Statistics*, *28*, 597-619. doi:10.1007/s00180-012-0319-z

Callegaro, M., Baker, R., Bethlehem, J., Göritz, A. S., Krosnick, J. A., & Lavrakas, P. J. (2014). *Online panel research. Online panel research: A data quality perspective.* doi:10.1002/9781118763520.

Castro, V., Garcia, E. E., Cavazos, J., Jr., & Castro, A. Y. (2011). The road to doctoral success and beyond. *International Journal of Doctoral Studies*, *6*, 51-77. Retrieved from http://www.ijds.org

Catapano, J. (2012). Tying credentialing to health care technology. *Physician Executive*, *38*(6), 42-46. Retrieved from http://www.acpe.org/publications/pej.aspx

Centers for Medicare and Medicaid Services. (2014). *Historical*. Retrieved from http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsHistorical.html

Cheng, P., Goldschmied, J., Deldin, P., Hoffmann, R., & Armitage, R. (2015). The role of fast and slow EEG activity during sleep in males and females with major depressive disorder. *Psychophysiology*, *228*(3). doi:10.1111/psyp.12472

Choi, Y. (2015). *Analyzing tagging patterns by integrating visual analytics with the inferential test.* In Proceedings of the 15th ACM/IEEE-CE on Joint Conference on Digital Libraries (pp. 255-256). doi:10.1145/2756406.2756962

Cleverley, W. O., Son, P. H., & Cleverley, J. O. (2012). *Essentials of health care finance* (7th ed.). Sudbury, MA: Jones and Bartlett.

Conklin, J. R., Togami, J. C., Burnett, A., Dodd, M. A., & Ray, G. M. (2014). Care transitions service: A pharmacy-driven program for medication reconciliation scores through the continuum of care. *American Journal of Health-System Pharmacy*, *71*, 802-810. doi:10.2146/ajhp130589

Cornett, B., & Latimer, T. M. (2011). Managing hospital readmissions: An overview of the issues. *Journal of Health Care Compliance*, *13*(6), 5-14. Retrieved from http://www.healthcarecompliance.us/journal-of-health-care-compliance.html

Coustasse, A., Shaffer, J., Conley, D., Coliflower, J., Deslich, S., & Sikula, A. (2013). Computer physician order entry (CPOE): Benefits and concerns-a status report. *Journal of Information Technology Research, 6*(3), 16-31. doi:10.4018/jitr.2013070102

Dahlöf, C. (2013). Ethical considerations in biomedical research: A personal view. *Cephalalgia*, *33*, 507-511. doi:10.1177/0333102412468674

Dalal, D. K., & Zickar, M. J. (2012). Some common myths about centering predictor variables in moderated multiple regression and polynomial regression. *Organizational Research Methods*, *15*, 339-362. doi:10.1177/1094428111430540

Davis, K., Schoen, C., & Stremikis, K. (2010). *How the performance of the U.S. health care system compares internationally*. New York, NY: The Commonwealth Fund.

DeLia, D., Jian, T., Gaboda, D., & Casalino, L. P. (2014). Post-discharge follow-up visits and hospital utilization by Medicare patients, 2007–2010. *Medicare & Medicaid Research Review*, *4*(2), E1-E19. doi:10.5600/mmrr.004.02.a01

Detmer, D. E. (2010). Engineering information technology for actionable information and better health. *Information Knowledge Systems Management, 8,* 107-118. doi:10.3233/IKS-2009-0138

Devaraj, S., Ow, T. T., & Kohli, R. (2013). Examining the impact of information technology and patient flow on healthcare performance: A theory of swift and even flow (TSEF) perspective. *Journal of Operations Management*, *31*, 181-192. doi:10.1016/j.jom.2013.03.001

Dewan, A. M., Corner, R. J., & Hashizume, M. (2014). Modeling spatiotemporal patterns of typhoid cases between 2005 and 2009 using spatial statistics. *In Dhaka Megacity, 11*, 345-365. doi:10.1007/978-94-007-6735-5

Dewan, S., & Ren, F. (2011). Information technology and firm boundaries: Impact on firm risk and return performance. *Information Systems Research, 22*, 368-388. doi:10.1287/isre.1090.0261

Dewan, S., & Ren, F. (2011). Information technology and firm boundaries: Impact on firm risk and return performance. *Information Systems Research, 22*, 369-388. Retrieved from https://www.informs.org/journal/isre

De Witte, N., Gobbens, R., De Donder, L., Dury, S., Buffel, T., Schols, J., & Verté, D. (2013). The comprehensive frailty assessment instrument: development, validity and reliability. *Geriatric Nursing*, *34*, 274-281. Retrieved from http://dx.doi.org/10.1016/j.gerinurse.2013.03.002

Dietz, J., Antonakis, J., Hoffrage, U., Krings, F., Marewski, J. N., & Zehnder, C. (2014). Teaching evidence-based management with a focus on producing local evidence. *Academy of Management Learning & Education, 13*, 397-414. doi:10.5465/amle.2013.0197

Dikolli, S. S., Evans, J. H., III, Hales, J., Matejka, M., Moser, D. V., & Williamson, M. G. (2012). Testing, analytical models using archival or experimental methods. *Accounting Horizons, 27*, 129-139. Retrieved from http://dx.doi.org/10.2308/acch-50287

Dilwali, P. K. (2013). From acute care to home care: The evolution of hospital responsibility and rationale for increased vertical integration. *Journal of Healthcare Management, 58*, 267-276. Retrieved from http://www.ache.org/pubs/jhm/jhm_index.cfm

Dong, L., Mitchell, T. R., Lee, T. W., Holtom, B. C., & Hinkin, T. R. (2012). When employees are out of step with coworkers: How job satisfaction trajectory and dispersion influence individual- and unit-level voluntary turnover. *Academy of Management Journal*, *55*, 1360-1380. doi:10.5465/amj.2010.0920

Doove, L. L., Van Buuren, S., & Dusseldorp, E. (2014). Recursive partitioning for missing data imputation in the presence of interaction effects. *Computational Statistics & Data Analysis, 72,* 92-104. doi:10.1016/j.csda.2013.10.025

Dos Santos, B. L., Zheng, Z., Mookerjee, V. S., & Chen, H. (2012). Are new IT-enabled investment opportunities diminishing for firms? *Information Systems Research, 23*, 287-305. doi:10.1287/isre.1110.0370

Dovonon, P., Goncalves, S., & Meddahi, N. (2013). Bootstrapping realized multivariate volatility measures. Journal of Econometrics, *172*(1), 49-65. doi 10.1007/978-1-4614-7750-1,

Ellenbecker, C. H., & Cushman, M. (2012). Home healthcare nurse retention and patient outcome model: Discussion and model development. *Journal of Advanced Nursing, 68*, 1881-1893. doi:10.1111/j.1365-2648.2011.05889.x

Esfahani, S., & Dougherty, E. R. (2014). Effect of separate sampling on classification accuracy. *Bioinformatics, 30*, 242-250. doi:10.1093/bioinformatics/btt662

Faisel, Y. (2010). Statistics using SPSS: An integrative approach, second edition. *Journal of Applied Statistics, 37,* 2119-2120. doi:10.1080/02664760903075515

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, *41*, 1149-1160. doi:10.3758/brm.41.4.1149

Fiske, S. T., & Hauser, R. M. (2014). Protecting human research participants in the age of big data. *Proceedings of the National Academy of Sciences*, *111*, 13675-13676. doi:10.1073/pnas.1414626111

Fletcher, J. F. (2013). *The impact of a readmission prevention team on hospital readmission rates* (Doctoral dissertation). Retrieved from ProQuest Dissertations and Theses Database. (3608184)

Ford, E. W., Huerta, T. R., Thompson, M. A., & Patry, R. (2011). The impact of accelerating electronic prescribing on hospitals' productivity levels: Can health information technology bend the curve? *Inquiry*, *48*, 304-312. doi:10.5034/inquiryjrnl_48.04.04

Ford, J. B., Algert, C. S., Morris, J. M., & Roberts, C. L. (2012). Decreasing the length of maternal hospital stay is not associated with increased readmission rates. *Australian & New Zealand Journal of Public Health*, *36*, 430-434. doi:10.1111/j.1753-6405.2012.00882.x

Freymann Fontenot, S. (2014). The Affordable Care Act and electronic health care records: Can technology help reduce the cost of health care? *Physician Executive*, *40*, 68-72. Retrieved from http://www.acpe.org/publications/pej.aspx

Friedman, B., Jiang, H., Steiner, C. A., & Bott, J. (2012). The likelihood of hospital readmission after first discharge: Medicare Advantage vs. fee-for-service patients. *Inquiry*, *49*, 202-213. doi:10.5034/inquiryjrnl_49.03.01

Gadermann, A. M., Guhn, M., & Zumbo, B. D. (2012). Estimating ordinal reliability for Likert-type and ordinal item response data: A conceptual, empirical, and practical guide. *Practical Assessment, Research & Evaluation*, *17*(3), 1-13. doi:10.1016/j.psychsport.2015.09.002

Gaskin, C. J., & Happell, B. (2014). Power, effects, confidence, and significance: An investigation of statistical practices in nursing research. *International Journal of Nursing Studies*, *51*, 795-806. doi:10.1016/j.ijnurstu.2013.09.014

Gerhardt, G., Yemane, A., Hickman, P., Oelschlaeger, A., Rollins, E., & Brennan, N. (2013). Medicare readmission rates showed a meaningful decline in 2012. *Medicare & Medicaid Research Review*, *3*(2), E1-E11. doi:10.5600/mmrr.003.02.b01

Germain, R., Davis-Sramek, B., Lonial, S. C., & Raju, P. S. (2011). The impact of relational supplier exchange on financial performance: A study of the hospital sector. *Journal of Business Logistics*, *32*, 240-253. doi:10.1111/j.2158-1592.2011.01020.x

Glenister, D. A. (2011). *Towards a general system theory in nursing: A literature review*. *Proceedings of the 55th annual meeting of the ISSS-2011.* Retrieved from http://journals.isss.org

Goldfield, N. I., McCullough, E. C., Hughes, J. S., Tang, A. M., Eastman, B., Rawlins, L. K., & Averill, R. F. (2008). Identifying potentially preventable re-admissions. *Health Care Financing Review, 30*, 75-91. Retrieved from http://www.cms.gov

Goldstein, H., Carpenter, J. R., & Browne, W. J. (2014). Fitting multivariate multilevel models with missing data in responses and covariates that may include interactions and non-linear terms. *Journal of the Royal Statistical Society, 177*, 553-564. doi:10.1111/rssa.12022

Goodman, J. K., Cryder, C. E., & Cheema, A. (2013). Data collection in a flat world: The strengths and weaknesses of Mechanical Turk samples. *Journal of Behavioral Decision Making, 26*, 213-224. Retrieved from http://apps.olin.wustl.edu/workingpapers/pdf/2012-02-002.pdf

Gravetter, F. J., & Wallnau, L. B. (2008). *Essentials of statistics for the behavioral sciences* (6th ed.). Belmont, CA: Thomson Wadsworth.

Green, S. B., Thompson, M. S., Levy, R., & Lo, W. J. (2015). Type I and Type II Error Rates and Overall Accuracy of the Revised Parallel Analysis Method for Determining the Number of Factors. *Educational and Psychological Measurement*, *75*, 428-457. doi: 10.1177/0013164414546566

Griffiths, P., & Norman, I. (2013). Qualitative or quantitative? Developing and evaluating complex interventions: time to end the paradigm war. *International Journal of Nursing Studies, 50*, 583-584. doi:10.1016/j.ijnurstu.2012.09.008

Grobler, A. C., Matthews, G., & Molenberghs, G. (2014). The impact of missing data on clinical trials: a re-analysis of a placebo-controlled trial of Hypericum perforatum (St John's wort) and sertraline in major depressive disorder. *Psychopharmacology, 231*, 1987-1999. doi:10.1007/s00213-013-3344-x

Handley, M. A., Schillinger, D., & Shiboski, S. (2011). Quasi-experimental designs in practice-based research settings: design and implementation considerations. *The Journal of the American Board of Family Medicine*, *24*, 589-596. doi:10.3122/jabfm.2011.05.110067

Harvath, B. S., Hilu, K., Nemana, R., & Sairamesh, R. (2013). Using technology to reduce readmissions. *Healthcare Financial Management*, *67*(12), 1-4. Retrieved from http://www.hfma.org/

Hayes, A. F., & Preacher, K. J. (2014). Statistical mediation analysis with a multicategorical independent variable. *British Journal of Mathematical and Statistical Psychology*, *67*, 451-470. doi:10.1111/bmsp.12028

Hays, D. G., & Wood, C. (2011). Infusing qualitative traditions in counseling research designs. *Journal of Counseling & Development, 89*, 288-295. doi:10.1002/j.1556-6678.2011.tb00091.x

Healthcare Financial Management. (2013). Hospitals facing FY14 readmission penalties revealed. *Healthcare Financial Management*, *67*(9), 11-13. Retrieved from http://www.hfma.org/

Hertlein, K. M., & Ancheta, K. (2014). Advantages and disadvantages of technology in relationships: Findings from an open-ended survey. *The Qualitative Report, 19*(11), 1-11. doi10.1080/2F01926187.2013.866511

Hieronymi, A. (2013). Understanding systems science: A visual and integrative approach. *Systems Research & Behavioral Science*, *30*, 580-595. doi:10.1002/sres.2215

Hoisington, A. (2012). Medication reconciliation scores drive readmission reduction strategy. *Managed Healthcare Executive*, *22*(12), 12-14. Retrieved from http://managedhealthcareexecutive.modernmedicine.com/

Holmes, W. H., & Rinaman, W. C. (2014). Multiple linear regression. In *Statistical literacy for clinical practitioners* (pp. 367-396). Berlin, Germany: Springer. doi:10.1007/978-3-319-12550-3_14

Hug, B. L., Keohane, C., Seger, D. L., Yoon, C., & Bates, D. W. (2012). The costs of adverse drug events in community hospitals. *Joint Commission Journal on Quality and Patient Safety, 38,* 120-126. Retrieved from http://edoc.unibas.ch/dok/A6205211

Hui, C. (2014). Secondary analysis of existing data: opportunities and implementation *Shanghai Arch Psychiatry, 26,* 371-375. doi:10.11919/j.issn.1002-0829.214171

Hume, K., & Tomsik, E. (2014). Enhancing patient education and medication reconciliation scores strategies to reduce readmission rates. *Hospital Pharmacy, 49,* 112-114. doi:10.1310/hpj4902-112

Jahedi, S., & Méndez, F. (2014). On the advantages and disadvantages of subjective measures. *Journal of Economic Behavior & Organization*, *98*, 97-114. doi:10.1016/j.jebo.2013.12.01

Jiang, C., Ni, B. Y., Han, X., & Tao, Y. R. (2014). Non-probabilistic convex model process: A new method of time-variant uncertainty analysis and its application to structural dynamic reliability problems. *Computer Methods in Applied Mechanics and Engineering*, *268*, 656-676. doi:10.1016/j.cma.2013.10.016

Johnson, D. E. (1990). The behavioral system model for nursing. In *Nursing theories in practice* (pp. 23-32). New York, NY: National League for Nursing. Retrieved from http://dx.doi.org/10.1037/0033-295X.106.3.458

Jones, C. (2010). Archival data: Advantages and disadvantages for research in psychology. *Social and Personality Psychology Compass, 4*, 1008-1017. doi/10.1111/j.1751-9004.2010.00317.x

Jones, E. B., & Furukawa, M. F. (2014). Adoption and use of electronic health records among federally qualified health centers grew substantially during 2010–2012. *Health Affairs, 33*, 1254-1261. Retrieved from http://content.healthaffairs.org/content/33/7/1254.short

Joynt, K. E., & Jha, A. K. (2011). Who has higher readmission rates for heart failure, and why? Implications for efforts to improve care using financial incentives. *Circulation: Cardiovascular Quality and Outcomes, 4*, 53-59. Retrieved from http://circoutcomes.ahajournals.org

Joynt, K. E., & Jha, A. K. (2012). Thirty-day readmissions—truth and consequences. *New England Journal of Medicine*, *366*, 1366-1369. doi:10.1056/NEJMp1201598

Karahanna, E., & Preston, D. S. (2013). The effect of social capital of the relationship between the CIO and top management team on firm performance. *Journal of Management Information Systems*, *30*, 15-56. doi:10.2753/MIS0742-1222300101

Kaufman, N. S. (2013). Net revenue per adjusted discharge continues to drive success. *Journal of Healthcare Management, 58*, 8-11. Retrieved from http://www.ache.org/pubs/jhm/jhm_index.cfm

Kazley, A., Diana, M., & Menachemi, N. (2011). The agreement and internal consistency of national hospital EMR measures. *Health Care Management Science*, *14*, 307-313. doi:10.1007/s10729-011-9165-8

Kessler, D. (2011). Evaluating the medical malpractice system and options for reform. *Journal of Economic Perspectives*, *25*, 93-110. doi:10.1257/jep.25.2.93

Kessler, R., & Glasgow, R. E. (2011). A proposal to speed the translation of healthcare research into practice: Dramatic change is needed. *American Journal of Preventive Medicine*, *40*, 637-644. doi:10.1016/j.amepre.2011.02.023

Ketterer, M. W., Draus, C., McCord, J., Mossallam, U., & Hudson, M. (2014). Behavioral factors and hospital admissions/readmissions in patients with CHF. *Psychosomatics, 55*, 45-50. doi:10.1016/j.psym.2013.06.019

Kirby, E. G. (2012). Strategic groups and outcomes in the US hospice care industry. *Journal of Health Organization and Management, 26*, 641-654. doi:10.1108/14777261211256954

Kohli, R., Devaraj, S., & Ow, T. T. (2012). Does information technology investment influence a firm's market value? A case of non-publicly traded healthcare firms. *MIS Quarterly*, *36*, 1145-1163. Retrieved from http://misq.org/

Kühberger, A., Fritz, A., Lermer, E., & Scherndl, T. (2015). The significance fallacy in inferential statistics. *BMC Research Notes*, *8*(1), 84-90. doi:10.1186/s13104-015-1020-4

Kwan, J. L., Lo, L., Sampson, M., & Shojania, K. G. (2013). Medication reconciliation during transitions of care as a patient safety strategy: A systematic review. *Annals of Internal Medicine, 158*, 397-403. doi:10.7326/0003-4819-158-5-201303051-00006

Lam, S. (2010). What kind of assumptions need to be realistic and how to test them: A response to Tsang. *Strategic Management Journal, 31*, 679-687. doi:10.1002/smj.832

Laugaland, K., Aase, K., & Barach, P. (2012). Interventions to improve patient safety in transitional care: A review of the evidence. *Work*, *41,* 2915-2924. Retrieved from http://www.iospress.nl

Leapfrog. (2014). *Leapfrog Hospital Survey.* Retrieved from https://leapfroghospitalsurvey.org/cpoe-evaluation-tool/

Lee, A., Varma, A., Boro, M., & Korman, N. (2014). The value of pharmacist medication interviews on optimizing the electronic medication reconciliation scores process. *Hospital Pharmacy*, *49*, 530-538. doi:10.1310/hpj4906-530

Lee, J., Tollefson, E., Daly, M., & Kielb, E. (2013). A generalized health economic and outcomes research model for the evaluation of companion diagnostics and targeted therapies. *Expert Review of Pharmacoeconomics & Outcomes Research, 13,* 361-370. doi:10.1586/erp.13.23

Lee, P., Andrade, D., Mastey, A., Sun, J., & Hicks, L. (2014). Institution-specific risk factors for 30-day readmission at a community hospital: A retrospective observational study. *BMC Health Services Research, 14*, 1-12. doi:10.1186/1472-6963-14-40

Leung, A. A., Keohane, C., Amato, M., Simon, S. R., Coffey, M., Kaufman, N., & Bates, D. W. (2012). Impact of vendor computerized physician order entry in community hospitals. *Journal of General Internal Medicine*, *27*, 801-807. doi:10.1007/s11606-012-1987-7

Li, M. X., Yeung, J. M., Cherny, S. S., & Sham, P. C. (2012). Evaluating the effective numbers of independent tests and significant p-value thresholds in commercial genotyping arrays and public imputation reference datasets. *Human Genetics*, *131*, 747-756. doi:10.1007/s00439-011-1118-2

Lier, B., & Hardjono, T. (2011). A systems theoretical approach to interoperability of information. *Systemic Practice & Action Research*, *24*, 479-497. doi:10.1007/s11213-011-9197

Linley, W., & Hughes, D. (2013). Decision-makers' preferences for approving new medicines in Wales: A discrete choice experiment with an assessment of external validity. *Pharmacoeconomics, 31*, 345-355. doi:10.1007/s40273-013-0030-0

Liu, D., Li, T., & Liang, D. (2014a). Incorporating logistic regression to decision-theoretic rough sets for classifications. *International Journal of Approximate Reasoning*, *55*, 197-210. doi:10.1016/j.ijar.2013.02.013

Liu, D. J., Peloso, G. M., Zhan, X., Holmen, O. L., Zawistowski, M., Feng, S., & Peters, U. (2014b). Meta-analysis of gene-level tests for rare variant association. *Nature Genetics, 46*, 200-204. doi:10.1038/ng.2852

Loomis, J. M. (2014). Three theories for reconciling the linearity of egocentric distance perception with distortion of shape on the ground plane. *Psychology & Neuroscience, 7*, 245-230. doi:10.3922/j.psns.2014.034

Luo, Z., Atamturktur, S., & Juang, C. H. (2012). Bootstrapping for characterizing the effect of uncertainty in sample statistics for braced excavations. *Journal of Geotechnical and Geoenvironmental Engineering, 139*(1), 13-23. Retrieved from http://dx.doi.org/10.1061/(ASCE)GT.1943-5606.0000734

Macy, M. L., Hall, M., Shah, S. S., Harding, J. P., Del Beccaro, M. A., Hain, P. D., & Alpern, E. R. (2012). Pediatric observation status is we overlooking a growing population in children's hospitals? *Journal of Hospital Medicine, 7,* 530-536. doi:10.1002/jhm.1923

Mark, T., Tomic, K., Kowlessar, N., Chu, B., Vandivort-Warren, R., & Smith, S. (2013). Hospital readmission among Medicaid patients with an index hospitalization for mental and substance use disorder. *Journal of Behavioral Health Services & Research*, *40*, 207-221. doi:10.1007/s11414-013-9323-5

McCormack, R., Michels, R., Ramos, N., Hutzler, L., Slover, J. D., & Bosco, J. A. (2013). Thirty-day readmission rates as a measure of quality: Causes of readmission after orthopedic surgeries and accuracy of administrative data. *Journal of Healthcare Management*, *58*, 64-76. Retrieved from http://www.ache.org/Publications/SubscriptionPurchase.aspx#jhm

McHugh, M. D., Berez, J., & Small, D. S. (2013). Hospitals with higher nurse staffing had lower odds of readmissions penalties than hospitals with lower staffing. *Health Affairs*, *32*, 1740-1747. doi:10.1377/hlthaff.2013.0613

McHugh, M. D., Carthon, J. L., & Kang, X. L. (2010). Medicare readmissions policies and racial and ethnic health disparities: A cautionary tale. *Policy, Politics, & Nursing Practice, 11*, 309-316. doi:10.1177/1527154411398490.

McNair, P. D., & Luft, H. S. (2012). Enhancing Medicare's hospital-acquired conditions policy to encompass readmissions. *Medicare & Medicaid Research Review*, *2*(2), E1-E14. doi:10.5600/mmrr.002.02.a03

Moran, G., Mashiach-Eizenberg, M., Roe, D., Berman, Y., Shalev, A., Kaplan, Z., & Epstein, P. G. (2014). Investigating the anatomy of the helping relationship in the context of psychiatric rehabilitation: The relation between working alliance, providers' recovery competencies, and personal recovery. *Psychiatry Research*, *220*, 592-597. doi:10.1016/j.psychres.2014.08.004

Morley, M., Bogasky, S., Gage, B., Flood, S., & Ingber, M. J. (2014). Medicare post-acute care episodes and payment bundling. *Medicare & Medicaid Research Review*, *4*, E1-E13. doi:10.5600/mmrr.004.01.b02

Moussa, M. N. (2013). Effects of perceived procedural justice and exchange ideology on employees' affective commitment: Evidence from Saudi Arabia. *International Journal of Business & Management*, *8*(15), 81-89. doi:10.5539/ijbm.v8n15p81

Murphy, S. M., Rosenman, R., McPherson, M. Q., & Friesner, D. L. (2011). Measuring shared inefficiency between hospital cost centers. *Medical Care Research and Review, 68*, 55S-74S. doi:10.1177/1077558710379224

Nimon, K. F., & Oswald, F. L. (2013). Understanding the results of multiple linear regression beyond standardized regression coefficients. *Organizational Research Methods*, *7*, 452-471. doi:10.1177/1094428113493929

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education, 15*, 625-632. doi:10.1007/s10459-010-9222

Norris, J. M., Plonsky, L., Ross, S. J., & Schoonen, R. (2015). Guidelines for reporting quantitative methods and results in primary research. *Language Learning*, *65*, 470-476. doi:10.1111/lang.12104

O'Leary, K., Kulkarni, N., Landler, M., Jeon, J., Hahn, K., Englert, K., & Williams, M. (2010). Hospitalized patients' understanding of their plan of care. *Mayo Clinic Proceedings, 85*(3), 47-52. Retrieved from http://www.mayoclinic.org/

Pallant, J. (2010). *SPSS survivor manual* (4th ed.). Berkshire. England: McGraw-Hill.

Rahman, M. A. (2013). Household characteristics and poverty: A logistic regression analysis. *Journal of Developing Areas, 47,* 303-317. doi:10.1353/jda.2013.0001

Rapaport, M. H., Judd, L. L., Schettler, P. J., Yonkers, K. A., Thase, M. E., Kupfer, D. J., & Rush, A. J. (2014). A descriptive analysis of the minor depression. *Focus*, *4*, 637-643. Retrieved from http://www.ids-qids.org/index2.html

Raudenbush, S. E., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2ndnd ed.). Thousands Oak, CA: Sage Publications

Räz, T., & Sauer, T. (2015). Outline of a dynamical inferential conception of the application of mathematics. *Studies in History and Philosophy of Science Part B: Studies in History and Philosophy of Modern Physics, 49,* 57-72. doi:10.1016/j.shpsb.2015.01.004

Reilly, G., Nyberg, A. J., Maltarich, M., & Weller, I. (2014). Human capital flows: Using context-emergent turnover (CET) theory to explore the process by which turnover, hiring, and job demands affect patient satisfaction. *Academy of Management Journal*, *57*, 766-790. doi:10.5465/amj.2012.0132

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin, 138,* 253-387. doi:10.1037/a0026838

Ripley, B., & Vieira, M. (2013). A collaborative approach to electronic medication reconciliation scores improvement. *Formulary*, *48*, 187-188. Retrieved from http://formularyjournal.modernmedicine.com/

Robinson, G., Parker, M., Kranenburg, T. A., Lu, C., Chen, X., Ding, L., & Chalhoub, N. (2012). Novel mutations target distinct subgroups of medulloblastoma. *Nature, 488*(7409), 43-48. doi:10.1038/nature11213

Roe, B. E., & Just, D. R. (2009). Internal and external validity in economics research: Tradeoffs between experiments, field experiments, natural experiments, and field data. *American Journal of Agricultural Economics, 91,* 1266-1271. doi:10.1111/j.1467-8276.2009.01295.x

Roussel, L., Swansburg, R. J., & Swansburg, R. C. (2006). *Management and leadership for nurse administrators*. Sudbury, MA: Jones & Bartlett.

Rozin, P., Hormes, J. M., Faith, M. S., & Wansink, B. (2012). Is meat male? A quantitative multimethod framework to establish metaphoric relationships. *Journal of Consumer Research*, *39*, 629-643. doi:10.1086/664970

Rubin, D. B., Singh, S., & Jacobson, P. D. (2013). Evaluating hospitals' provision of community benefit: An argument for an outcome-based approach to nonprofit hospital tax exemption. *American Journal of Public Health*, *103*, 612-616. doi:10.2105/AJPH.2012.301048

Scott, S. D., Albrecht, L., O'Leary, K., Ball, G. D., Hartling, L., Hofmeyer, A., & Dryden, D. M. (2012). Systematic review of knowledge translation strategies in the allied health professions. *Implementation Science*, *7*(1), 70-75. doi:10.1186/17485908-7-70

Segal, M., Rollins, E., Hodges, K., & Roozeboom, M. (2014). Medicare-Medicaid eligible beneficiaries and potentially avoidable hospitalizations. *Medicare & Medicaid Research Review*, *4*, E1-E12. doi:10.5600/mmrr.004.01.b01

Sen, S., Siemianowski, L., Murphy, M., & McAllister, S. (2014). Implementation of a pharmacy technician-centered medication reconciliation scores program at an urban teaching medical center. *American Journal of Health-System Pharmacy*, *71*, 51-56. doi:10.2146/ajhp130073

Senge, P. M., Carstedt, G., & Porter, P. L. (2001). *Next industrial revolution*. Cambridge, MA: MIT Sloan Management Review.

Setia, P., Setia, M., Krishnan, R., & Sambamurthy, V. (2011). The effects of the assimilation and use of IT applications on financial performance in healthcare organizations. *Journal of the Association for Information Systems*, *12*, 274-298. Retrieved from http://aisel.aisnet.org/jais/

Shahian, D. M., Nordberg, P., Meyer, G. S., Blanchfield, B. B., Mort, E. A., Torchiana, D. F., & Normand, S. L. T. (2012). Contemporary performance of US teaching and nonteaching hospitals. *Academic Medicine*, *87*, 701-708. doi:10.1097/ACM.0b013e318253676a.

Shaw, E. (2014). The quest for a general theory of the marketing system. *Journal of Historical Research in Marketing*, *6*, 523-537. doi:10.1108/JHRM-07-2013-0041

Shulan, M., Gao, K., & Moore, C. (2013). Predicting 30-day all-cause hospital readmissions. *Health Care Management Science*, *16*, 167-175. doi:10.1007/s10729-013-9220-8

Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). P-curve: A key to the file-drawer. *Journal of Experimental Psychology: General, 143*, 534-540. Retrieved from http://dx.doi.org/10.1037/a0033242

Singh, S. R., Wheeler, J., & Roden, K. (2012). Hospital financial management: What is the link between revenue cycle management, profitability, and not-for-profit hospitals' ability to grow equity? *Journal of Healthcare Management, 57*, 325-339. Retrieved from http://www.ache.org/pubs/jhm/jhm_index.cfm

Smith, A. L., Bradley, R. V., Bichescu, B. C., & Tremblay, M. (2013). IT governance characteristics, electronic medical records sophistication, and financial performance in U.S. hospitals: An empirical investigation. *Decision Sciences*, *44*, 483-516. doi:10.1111/deci.12019

Sofowote, U., Su, Y., Bitzos, M. M., & Munoz, A. (2014). Improving the correlations of ambient tapered element oscillating microbalance PM2. 5 data and SHARP 5030 federal equivalent method in Ontario: A multiple linear regression analysis. *Journal of the Air & Waste Management Association*, *64*, 104-114. doi:10.1080/10962247.2013.833145

Sowinski, C., LeFevre, J. A., Skwarchuk, S. L., Kamawar, D., Bisanz, J., & Smith-Chant, B. (2015). Refining the quantitative pathway of the pathways to mathematics model (PMID:25521665). *Journal of Experimental Child Psychology*, *131*, 73-93. doi:10.1016/j.jecp.2014.11.004

Sparks, J. R., & Pan, Y. (2010). Ethical judgments in business ethics research: Definition, and research agenda. *Journal of Business Ethics, 91*, 405-418. doi:10.1007/s10551-009-0092-2

Spaulding, T. J., & Raghu, T. (2013). The impact of CPOES usage on medication management process costs and quality outcomes. *Inquiry, 50*, 229-247. doi:10.1177/0046958013519303

Statistics Brain. (2013). *Healthcare industry statistics.* Retrieved from http://www.statisticbrain.com/health-care-industry-statistics/

Stewart, A. L., & Lynch, K. J. (2014). Medication discrepancies despite pharmacist-led medication reconciliation: the challenges of maintaining an accurate medication list in primary care. *Pharmacy Practice*, *12*, 1-7. Retrieved from http://www.pharmacypractice.org/

Sullivan, G. M., & Feinn, R. (2012). Using effect size-or why the P value is not enough. *Journal of Graduate Medical Education, 4*, 279-282. Retrieved from http://dx.doi.org/10.4300/JGME-D-12-00156.1

Tabachnick, B. G. and Fidell, L. S. (2007). *Using Multivariate Statistics* (5th Ed.). Boston: Allyn and Bacon.

Thompson, D. (2014). U.S. hospital CPOE adoption reaches 50 percent—benefits to follow. *Health Management Technology*, *35*(2), 27-28. Retrieved from http://www.healthmgttech.com/

Tootelian, D. H., Negrete, M., & Skhal, J. T. (2010). The “sandwich mom”: In the throes of a medication safety “perfect storm.” *Health Marketing Quarterly*, *27*, 307-320. doi:10.1080/07359683.2010.49530

University of Wisconsin-Eau Claire. (2014). *Data collection methods*. Retrieved from http://people.uwec.edu/piercech/ResearchMethods/Data%20collection%20methods/DATA%20COLLECTION%20METHODS.htm

U.S. Census Bureau. (2012). *Health and nutrition: Healthcare resources.* Retrieved from http://www.census.gov/compendia/statab/cats/healthnutrition /health _care_ resources.html

Valentinov, V. (2012). The institutionalist implications of the general systems theory: The societal role of the market. *Systems Research & Behavioral Science*, *29*, 253-262. doi:10.1002/sres.1129

Valeri, L., & VanderWeele, T. J. (2013). Mediation analysis allowing for exposure–mediator interactions and causal interpretation: Theoretical assumptions and implementation with SAS and SPSS macros. *Psychological Methods*, *18*, 137-143. Retrieved from http://dx.doi.org/10.1037/a0031034

van Deventer, J. (2009). Ethical considerations during human-centered overt and covert research. *Quality and Quantity, 43*, 45-57. doi:10.1007/s11135-006-9069-8

Vartian, C. V., Singh, H., DeBakey, M. E., Russo, E., & Sittig, D. F. (2014). Development and field-testing of a self-assessment guide for computer-based provider order entry. *Journal of Healthcare Management*, *59*, 338-352. Retrieved from http://www.ache.org/pubs/jhmtoc.cfm

Venkatesh, V., Brown, S., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS Quarterly, 37*, 21-54. Retrieved from http://www.misq.org

Vertrees, J. C., Averill, R. F., Eisenhandler, J., Quain, A., & Switalski, J. (2013). Bundling post-acute care services into MS-DRG payments. *Medicare & Medicaid Research Review*, *3*(3), E1-E18. doi:10.5600/mmrr.003.03.a03

Vogenberg, F., & DiLascia, C. (2013). Medication reconciliation scores efforts meeting needs and showing promise. *Formulary*, *48*(5), 1-6. Retrieved from http://formularyjournal.modernmedicine.com/

Von Hippel, P. T. (2012). Biases in SPSS 12.0 missing value analysis. *The American Statistician, 58*, 160-164. doi:10.1198/0003130043204

Von Bertalannffy, L. (1972). The history and status of general systems theory. *Academy of Management Journal, 15*, 407-426. doi:10.2307/255139

Voyer, S. D., & Voyer, D. (2015). Laterality, spatial abilities, and accident proneness. *Journal of Clinical and Experimental Neuropsychology, 37*(1), 27-36. doi:10.1080/13803395.2014.985191

Walker, T. (2012a). Pharmacists must prioritize medication reconciliation. *Formulary*, *47*, 402-403. Retrieved from http://formularyjournal.modernmedicine.com/

Walker, T. (2012b). Take charge of medication reconciliation scores to reduce readmission rates. *Formulary*, *47*, 343-347. Retrieved from http://formularyjournal.modernmedicine.com/

Walonick, D. S. (1993). *General systems theory.* Retrieved from http://www.statpac.org/walonick/systems-theory.htm

Wang, C. J., & Huang, A. T. (2012). Integrating technology in health care: What will it take? *Journal of the American Medical Association, 307*, 569-570. doi:10.1001/jama.2012.102

Warden, B. A., Freels, J., Furuno, J. P., & Mackay, J. (2014). Pharmacy-managed program for providing education and discharge instructions for patients with heart failure. *American Journal of Health-System Pharmacy*, *71*, 134-139. doi:10.2146/ajhp130103

Watts, J. H. (2011). Ethical and practical challenges of participant observation in sensitive health research. *International Journal of Social Research Methodology, 14,* 301-312. doi:10.1080/13645579.2010.517658

Weiss, R. (2013). A remedy for readmissions. *Marketing Health Services*, *33*(2), 14-15. Retrieved from https://www.ama.org/publications/MarketingHealthServices

Wright, A., Henkin, S., Feblowitz, J., McCoy, A. B., Bates, D. W., & Sittig, D. F. (2013). Early results of the meaningful use program for electronic health records. *New England Journal of Medicine, 368*, 779-780. doi:10.1056/NEJMc1213481

Wu, S. (2013). A review on coarse warranty data and analysis. *Reliability Engineering & System Safety*, *114*, 1-11. doi:10.1016/j.ress.2012.12.021

Yayla, A. A., & Hu, Q. (2011). The impact of information security events on the stock value of firms: The effect of contingency factors. *Journal of Information Technology, 26*, 60-77. doi:10.1057/jit.2010.4

Yang, J., Zaitlen, N. A., Goddard, M. E., Visscher, P. M., & Price, A. L. (2014). Advantages and pitfalls in the application of mixed-model association methods. *Nature Genetics, 46*, 100-106. doi:10.1038/ng.2876

Ye, Y., Wu, Q., Huang, J. Z., Ng, M. K., & Li, X. (2013). Stratified sampling for feature subspace selection in random forests for high dimensional data. *Pattern Recognition, 46,* 769-787. doi:10.1016/j.patcog.2012.09.005

Yin, S., Zhu, X., & Kaynak, O. (2015). Improved PLS focused on key-performance-indicator-related fault diagnosis. *Industrial Electronics*, *62*, 1651-1658. doi:10.1109/TIE.2014.2345331

Zachariadis, M., Scott, S., & Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS Quarterly*, *37*, 855-879. Retrieved from www. misq.org

Zaman, K., Rangavajhala, S., McDonald, M. P., & Mahadevan, S. (2011). A probabilistic approach for representation of interval uncertainty. *Reliability Engineering & System Safety*, *96*, 117-130. doi:10.1016/j.ress.2010.07.012

Zhang, Y. A., & Shaw, J. D. (2012). Publishing in AMJ—Part 5: Crafting the methods and results. *Academy of Management Journal, 55*, 8-12. doi:10.5465/amj.2012.4001

Zhivan, N., & Diana, M. (2012). U.S. hospital efficiency and adoption of the health information technology. *Health Care Management Science*, *15*, 37-47. doi:10.1007/s10729-011-9179-2

Appendix A: Certificate of Completion

Certificate of Completion

The National Institutes of Health (NIH) Office of Extramural Research certifies that **Henry Carter** completed the NIH Web-based training course “Protecting Human Research Participants.”

Date of completion: 07/06/2012

Certification Number: 946255

Appendix B: Data User Agreement

THELEAPFROGGROUP

<u>RESEARCH DATA USE AGREEMENT</u>

THIS RESEARCH DATA USE AGREEMENT, (the "Agreement") dated _________ (the "Effective Date"), is between The Leapfrog Group, ("Leapfrog") and **Henry M. Carter**.

The parties agree to Researcher's use of the Leapfrog Hospital Survey data ("the Data") as follows:

1. Leapfrog agrees to release the Data to Researcher for the sole purpose of <u>**his quantitative correlational study that will examine the relationship between computerized physician order entry scores, medication reconciliation scores, and 30-day readmission rates for hospitals located in Alabama, Florida, and Georgia. Identifiers displaying hospitals names will be removed. The implications for positive social change include the potential for hospital administrators and other hospital officials to improve service to patients.**</u> The researcher shall not use or further disclose the Data, electronically or otherwise, other than as permitted by this Agreement or required by law. More specifically, Researcher shall not (i) distribute, publicize or provide the Data to any third party; (ii) use the Data on behalf of or for the benefit of any third party; and (iii) modify or create any derivative of the Data.

2. Researcher acknowledges and agrees that Leapfrog owns all rights, title and interest in and to the Data, and that Researcher has no rights, title or interest in the Data.

3. Researcher acknowledges and agrees that since the Data is based on data provided by third parties, it is reasonable that the Data and any services provided under this

Agreement be, and they are, AS IS, AS AVAILABLE and WITH ALL FAULTS. Leapfrog disclaims any and all warranties, express or implied, including any warranty of title, non-infringement, fitness for a particular purpose, merchantability or arising out of any course of dealing.

4. IN NO EVENT SHALL LEAPFROG BE LIABLE FOR ANY REASON ARISING OUT OF RESEARCHER'S USE OF THE DATA. IN NO EVENT SHALL LEAPFROG BE LIABLE FOR

UNDER THIS AGREEMENT OR ANY MATTER ARISING OUT OF OR RELATED TO THIS AGREEMENT OR RESEARCHER'S USE OF THE DATA. LEAPFROG SHALL NOT BE LIABLE FOR ANY LIABILITIES, DAMAGES, DEMANDS, COSTS (INCLUDING WITHOUT LIMITATION REASONABLE ATTORNEYS' FEES) OR CAUSES OF ACTION IN CONNECTION WITH ANY CLAIM BY RESEARCHER ARISING OUT OF OR RELATED TO THIS AGREEMENT.

5. Researcher agrees to allow Leapfrog to review in advance any article submitted for publication, any press announcements, or any other public materials based on the Data.

6. This Agreement shall terminate one year from the Effective Date. Upon termination of this Agreement, Researcher is obligated to return or destroy the Data that was provided up to the date of termination.

7. The confidentiality obligations shall survive any termination, cancellation or expiration of this Agreement.

IN WITNESS WHEREOF, the parties hereto have caused this Agreement to be signed in duplicate by Leapfrog's duly authorized officer, Faculty Advisor, and Researcher.

THE LEAPFROG GROUP

By (Signature): Leah Binder

Printed Name: Leah Binder

Title: President & CEO

Date: 4/4/2016

RESEARCHER

(Signature) Henry M. Carter

Printed Name: Henry M. Carter Student ID: A00233360

Title: Doctoral Student at Walden University

Date: 04/01/2016

WALDEN FACULTY

(Signature) Douglas G. Campbell Ph.D.

Printed Name: Douglas G. Campbell

Title: Senior Methodologist

Date: 4/5/2016

Appendix C: IRB Approval Number

The IRB approval number for this study is
03-31-16-0233360