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Inpatient Length of Stay, Readmission Rates, and Cost Burden: Financial Implications

Patricia Nneka Igboneje-Asor
Walden University

Walden University

College of Management and Human Potential

This is to certify that the doctoral study by

Patricia Nneka Igboneje-Asor

has been found to be complete and satisfactory in all respects,
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Review Committee
Dr. David Bull, Committee Chairperson, Health Sciences Faculty
Dr. Kourtney Nieves, Committee Member, Health Sciences Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2023

Abstract

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by

Patricia Igboneje-Asor

MSHA, South University, 2016

BA, Mercer University, 2013

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of

Healthcare Administration

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Abstract

The purpose of this quantitative descriptive correlational study was to investigate the financial implications of Length of Stay (LOS) and Readmission Rates (RR) on the cost of patient care (C) and to determine the extent of the relationship between the variables in Texas, United States. A secondary dataset from the Texas hospital data collection database of 920 hospitals was used, where 65 hospitals were included in the study following a G*Power analysis. Pearson correlation and regression analyses were conducted to explore the relationship between the variables at a 95% confidence interval. The findings showed a significant negative relationship between average length of stay (LOS) and average total cost (C), with Spearman's rho, $r = -.291$, $p = .019$. In addition, the results showed no statistically significant relationship between readmission rate (RR) and average total cost (C), with Spearman's rho, $r = .067$, $p = .594$. A multiple regression analysis showed that the regression model was not statistically significant, $F(2,62) = 1.591$, $p = .212$; hence, there was no need to interpret the coefficients. Thus, the LOS and RR do not necessarily predict the cost of care. The study implicates that there is a need for further research to evaluate factors affecting the cost of care in Texas hospitals since LOS and RR are not major predictors. The absence of a significant relationship between LOS, RR, and C does not necessarily indicate inefficiency or lack of effectiveness. Future research should consider the mediating and moderating factors that impact the relationship between LOS, RR, and C to understand their association better and inform strategies that healthcare facilities can employ to improve healthcare quality and reduce costs.

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Dedication

For the sake of God, my great teacher and messenger who taught me the purpose of life. And to my late parents, who have never failed to give me moral support and teachings that even the largest task could be accomplished if it was done one step at a time. I dedicate this project to all people who have worked hard to help me complete this dissertation.

Acknowledgments

I am very grateful to all those with whom I have had the pleasure to work during this period. Each member of my dissertation committee has provided me with extensive personal and professional guidance and taught me a great deal about the philosophy of life and leadership in general. I would especially like to thank Dr. David Bull, the chairman of my committee, as my teacher and mentor; he has taught me more than I could ever give him credit for here. He has shown me by his example what a great leader should be.

I also want to express my deep appreciation and indebtedness, particularly to the following.

Dr. & Dr. Mrs. Ezeabasili, Dr. Ben Nnadozie, Mrs. Nkechi Ugochukwu and Dr. James Agazie, for their endless support and kind and understanding spirit during this journey. To all my relatives, friends, and others who, in one way or another, shared their support, either morally, financially, or physically, thank you so much.

Above all, to my children, family, and grandchildren, to Great God Almighty, the author of knowledge and wisdom, for his countless love and peace. I thank you, God of Zion, the God of Eleven Hour.

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Section 1: Foundation of the Study and Literature Review

Introduction

The cost of care in the United States remains a concern to providers, patients, and third-party payers. Many people find it challenging to meet the cost of their medical care as bills pile up, driving many patients to financial hardship and bankruptcy. Social programs like Medicaid have also seen a dramatic rise in healthcare spending. The National Health Expenditure (NHE) showed tremendous increases in almost all responsibility areas in 2019. For example, the Center for Medicare and Medicaid (CMS) (2020) reported that the NHE grew 4.6% to $3.8 trillion in 2019, or $11,582 per person, and accounted for 17.7% of Gross Domestic Product (GDP); Medicare spending grew 6.7% to $799.4 billion in 2019; Medicaid spending grew 2.9% to $613.5 billion in 2019; Private health insurance spending grew 3.7% to $1,195.1 billion in 2019 (CMS, 2021). These statistics were among significant increases in healthcare expenditures, and the projection shows continued increases in the coming years.

The Organization for Economic Cooperation and Development (OECD, 2021) reported that the United States spends the most on healthcare per person annually. The OECD estimated that the U.S. spent about $10,586 per person in 2019, the highest globally and 42 percent higher than Switzerland (Kamal, Ramirez, Cox, 2020). Unfortunately, despite spending the most on healthcare, health outcomes in the United States were not better than in other countries. As a result, efforts have been sustained to stabilize costs or dramatically reduce the cost of care in the United States. Patients, providers, and the government seek to address this menace. In this light, the research was conducted to help identify some of these factors and recommend ways to address them.

The remainder of the chapter included the background of the study, problem statement, purpose of the study, research questions and hypothesis, nature of the study, literature search strategy, and literature review.

Background

The government of the United States, professional healthcare organizations, providers, and third-party payers have been concerned about the cost of care for the last three decades. Several strategies, including enforcing quality metrics, such as reduced length of stay (LOS), reduction of readmission rates (RR), pay-for-performance, and other quality metrics, were adopted to mitigate cost, yet the results were not encouraging. The CMS and other third-party payers have attached quality metrics to reimbursements to encourage quality care and reduce the cost of care. However, the cost of care continues to increase. As a result, cost-saving measures by legislators and providers tend to interfere with the quality of care and patient outcomes. Luhby (2021) reported that the Biden administration had taken dramatic steps to reduce healthcare costs in effect in early 2022. Luhby said that the "No Surprises Act," which banned unexpected medical charges from out-of-network providers, just went into effect on January 1, 2022. The law impacted over 10 million surprise bills annually, and it was one of the prominent consumer protection laws enacted in healthcare (Luhby, 2021).

The study examined LOS, RR, and the cost (C) burdens on patients, providers, and third-party payers. Previous studies have shown that reduced LOS and increased RR were directly related to poor quality of care and patient outcomes (Christensen, Grapetine, Pomputius, Spaulding, & 2019; Swelling, 2020; Wandella, 2017). The Institute of Medicine (IOM), now the National Academy of Medicine (NAM), outlined six goals for improving healthcare in the United States. The IOM (2001) recommended that healthcare be timely, safe, effective, efficient, equitable, and patient-centered. Despite these recommendations, the healthcare industry continuously faces challenges in meeting these overarching quality goals, resulting in a financial burden for providers, patients, and third-party payers. To meet these quality goals and avoid lawsuits and other unwanted outcomes, some providers sometimes turn to defensive medicine (Schneider, 2019). Defensive medicine has not only prolonged LOS and increased RRs but also induced financial burdens on patients, providers, and third-party payers (Vento, Cainelli, & Vallone, 2018). Defensive medicine ordered medical tests and procedures, including prolonged LOS and increased RR, to protect providers from malpractice suits. Sometimes, the health condition of patients may dictate LOS and RR. However, it was also important to note that some providers may want to observe patients a little longer, especially in teaching hospitals, for research purposes and to ensure better outcomes. These prolonged LOS and increased RR increase the cost of operations and quality indications.

The Center for Medicare and Medicaid (CMS) considers LOS and RR quality measures and has tied these two metrics to reimbursement rates. Likewise, the Organization for Economic Cooperation and Development (OECD, 2021) refers to the average length of hospital stay (ALOS) as an efficiency indicator. The OECD (2021) has resolved that a shorter stay reduces inpatient care costs in a hospital setting, while a prolonged LOS may increase costs. Similarly, a reduced RR saves costs, while an increased RR results in a higher total care cost (C) for the patient and the third-party payers (OECD, 2021).

As healthcare organizations strive to foster an environment of improved patient care in a timely, safe, efficient, and affordable way, deploying practices to reduce the cost of care may benefit the industry. The insight gained from this study aims to broaden the knowledge base, bridge the gap in the literature related to LOS and RR, and address social change by providing a more dynamic view of the complex interaction between LOS and RR and the financial implications posed to stakeholders. This dynamism may provide patients, third-party payers, healthcare leaders, physicians, researchers, and educators with enhanced learning supporting healthcare financing and management.

Problem Statement

Hospital inpatient length of stay and readmission rates have severe financial implications for stakeholders and the entire healthcare industry. The Affordable Care Act (ACA) mandates accountability and transparency in hospital operations. Many hospitals now reveal the financial stress they undergo due to increased RR and prolonged LOS. Due to mandatory reporting, transparency about the quality-of-care data was a growing issue for hospitals and health services organizations. Upadhyay, Stephenson, and Smith (2019) indicated that a reduction in readmission rates was related to increased operating revenues. Additionally, reducing readmission rates was also related to increased operating expenses. The authors noted that as readmissions continued, expenses gradually increased due to more significant resources, leading to decreased profitability.

In recent years, in response to the rapid cost inflation or reimbursements resulting in a massive financial burden for the CMS and other third-party payers within the health care sector, significant changes have been taking place in the structure of third-party payment systems for hospitals' medical services. One significant change has been the shift from open-ended payment systems based on costs or charges to a more controlled system that limits the volume of services. These new systems, which now form the Medicare prospective payment system's basis, have been instrumental in promoting providers' behavioral changes. Consequently, the interest in studying provider, patient, and third-party payer responses to payment incentives has increased dramatically, and any study in this direction was on the increase. The financial burden placed on third-party payers, patients, and providers due to increased readmissions and length of stay has been a problem for many healthcare stakeholders. Medicare and other third-party payers continue to look for consistent metrics to reimburse providers and have used metrics like geographical adjustments and severity of medical diagnoses (Wandella, 2017). There have been mixed results from several studies involving readmissions, length of stay, and cost burden on third-party payers, providers, and patients (Upadhyay, Stephenson, & Smith, 2019). The results have been some dissimilarity in reimbursement rates and a lack of financial consistency on the side of Medicare. Having consistent metrics based on data would be helpful for health services financial managers.

Upadhyay, Stephenson, and Smith (2019) have suggested conducting future studies to better understand the association between readmission rates and financial performance. It was generally expected that increased readmission may result in more expenditures from third-party payers and patients and more hospital income. However, Upadhyay, Stephenson, and Smith (2019) noted that readmissions did not lead to profitability for providers. The difference in research findings regarding LOS and RR, concerning Cost of care and reimbursement rates, results in a gap in knowledge from which healthcare decisions could be made. It was apparent that further investigation was needed to help provide a knowledge base from where valuable decisions could be made.

Purpose of the Study

The purpose of this quantitative study was to investigate the financial implications or the influence of Cost of patient care (C) – Dependent Variable (DV) on Length of Stay (LOS) and Readmission Rates (RR) – Independent Variables, respectively. The study further aims to examine the extent of the relationship between the variables in hospitals in Texas, a Southeastern state of the United States.

While researchers have investigated this issue (Upadhyay, Stephenson, and Smith, 2019; Wandella, 2017; Christensen, Spaulding, Pomputius, & Grapentine, 2019), there was a gap in knowledge around what was known about the relationships between all three. As cost remains the single concern for all healthcare stakeholders, the need to examine these triadic elements was further supported. In addition, further research has validated the complex interactions that occur among these three elements. Upadhyay et al. (2019) recommended that further studies be done to examine the relationship between

LOS, RR, and C, adding helpful insight to the literature that may further support healthcare managers and third-party payers in their attempt to provide quality care reasonably.

Research Questions and Hypotheses

Hospital readmission within 30 days of discharge was an important quality parameter of health care reform in the United States (Swilling, 2020). Health services providers, the Centers for Medicare and Medicaid (CMS), and other quality care organizations aimed to identify ways to improve the quality of care and patient outcomes cost-effectively by reducing 30-day readmission rates and length of stay. In addition, reducing readmission rates and length of stay without drastically impacting cost gives hospitals, patients, and third-party payers financial incentives. As a result, the thirty-day readmissions have become an essential measure of quality care and a target for reducing healthcare costs.

This study examines if the relationships exist between the length of stay, readmission rates, and cost of care and to what degree. This study further aims to understand better the financial implications of LOS and RR on providers, patients, and third-party payers.

The research questions and hypotheses formulated to guide this quantitative study were as follows:

RQ1: What was the relationship between the Cost of patient care (C) in Texas hospitals and Length of stay (LOS)?

*H*0: There was no significant relationship between the Cost of patient care (C) in Texas hospitals, length of stay (LOS).

*H*1: There was a significant relationship between the Cost of patient care (C) in Texas hospitals, and length of stay (LOS).

RQ2: What was the relationship between Cost of care (C) in Texas hospitals and readmission rates (RR)?

*H*0: There was no statistically significant relationship between the Cost of patient care (C) in Texas hospitals and readmission rates (RR).

*H*1: There was a statistically significant relationship between costs of patient care (C) and readmission rates (RR).

Theoretical Framework

This study was grounded in the Donabedian theory, in which quality care and patient outcomes were an integral function of evaluating the quality of care in healthcare institutions. In the Donabedian model, information about the quality of care could be drawn from three categories: "structure," "process," and "outcomes" (Donabedian, 1988). The model's structure represents the resources and facilities in place to facilitate care. The process represents the interactions between patients and providers. Finally, outcomes refer to the population's health condition due to the care provided to them. Donabedian's health care quality model stipulates that improvements in the structure of care should lead to improvements in clinical processes that should, in turn, improve patient outcomes (Donabedian, 1988).

The Donabedian model has been successfully used in several health quality studies (Berwick & Fox, 2016; Franklin, 2019; Ayanian & Markel, 2016). Structural processes include equipment, financial resources, human resources, and organizational structure effectively utilized to produce patient outcomes such as hospitalizations, cost, mortality, functional status, quality of life, and patient satisfaction (Franklin, 2019). A complimentary mix of these variables makes the Donabedian model a perfect fit for this study. Patient LOS, RR, and Cost of care were integral functions of the structure, process, and outcomes that form the fundamental fabric of any healthcare quality process in hospitals.

The mission of a health services organization was to provide patients with quality care, which could be facilitated through the structure, process, and outcome variables of the Donabedian model. If applied effectively in terms of attributes and behaviors in practice, the variables within the model align with driving positive patient outcomes. In the Donabedian theory, quality care and patient outcome frameworks are integral in evaluating patient care in healthcare institutions. According to the model, information about the quality of care in any healthcare setting could be drawn from three main categories: “structure,” “process,” and “outcomes.” The Structure component describes the context in which care was delivered, including hospital buildings, staff, financing, and equipment. The Process aspect denotes the transactions between patients and providers throughout healthcare delivery. Finally, Outcomes refer to the impact of the services delivered on the health status of patients and populations. The healthcare manager should relate to these three dimensions of the model meaningfully. The Donabedian model further stipulates that improvements in the structure of care should lead to improvements in clinical processes, which should improve patient outcomes (Donabedian, 2003).

The premise of the Donabedian theory was that a well-equipped hospital with qualified providers should produce better patient outcomes, including reduced length of stay, fewer readmissions, and hence reduced cost of care. Wandella (2017) reported that for providers, increased length of stay and readmission were often associated with poor quality, resulting in reimbursement problems, especially for Medicare. Wandella suggested that the source of longer hospitalization periods and higher re-admission rates among Medicare patients requires financial consistency or standardization, which Medicare has not realized for a while now. The Wandella recommended further investigating the phenomenon to help healthcare managers and other third payer payers, especially Medicare, make reliable decisions.

Moore et al. (2015) used the Donabedian model to evaluate the quality of care in a trauma hospital in Canada from 2005 to 2010 using quality indicators of readmission and hospital length of stay (LOS). The methodology was a quantitative descriptive correlation with Pearson's correlation coefficients. The researchers found statistically significant correlations between structure and process, process, and outcome. In addition, significant positive correlations were also observed between outcome, LOS, and readmissions. Therefore, Moore et al. (2015) disclosed the following: 1) Donabedian's structure-process-outcome model was a valid model for evaluating the variables, 2) the methodology revealed the association between research variables, and d) linear multiple regression would predict the action of one variable on another.

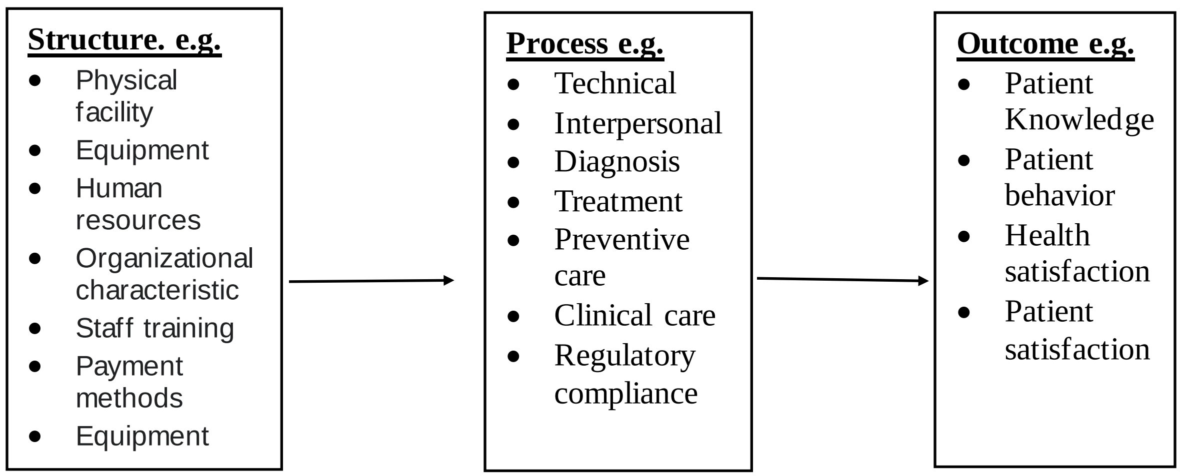
In another study, Binder et al. (2021) conducted a facility-level case study to describe leadership processes applying the Donabedian model to evaluate early response to the coronavirus pandemic relative to emergency care. Using the Donabedian model as a guide, Binder et al. used the Donabedian model as a guide to demonstrate that structure and process changes were implemented to maintain high-quality clinical outcomes and ensure emergency department staff safety and engagement. Binder, Torres, and Elwell reported that rapid changes to the model of care, both architecturally and through the expansion of universal precautions using personal protective equipment, created the foundation for staff and patient safety. Clinical, service quality, and staff safety outcomes were evaluated to demonstrate that the collaborative changes that follow a known process improvement model could be used to address the coronavirus disease pandemic. The Donabedian's structure-process-outcome quality of care model positively influences patient care outcomes. Therefore, this study used a similar methodology to investigate the relationship between length of stay, readmission rate, and healthcare cost.

The Donabedian Model Conceptual Framework

The original conceptualized model in figure 1 reveals a chain of activities categorized into the structure, process, and outcome connected by unidirectional arrows. Each variable consists of information that, when collected and analyzed, may provide valuable inferences about the quality of care in any healthcare facility (Donabedian, 2003). The direct relation of the model to the topic under investigation was that length of stay, readmission rates, and cost were integral parts of the CMS quality metrics for hospitals and other care facilities (CMS, 2021).

Figure 1

The Donabedian Model



The structure segment of the model describes the care environment, including the physical environment that makes it conducive for both the providers and patients. The process includes the technical and interpersonal care provided to the patients that may result in long or short lengths of stay, and the outcome denotes the patient's condition after receiving care. This outcome may lead to good health or warrant readmissions for other care, which has implications for cost for the patient and insurance companies. The Donabedian model was widely recognized and applied in many healthcare-related fields and was specifically developed to assess the quality of care in clinical practice (Donabedian, 2003).

Some quality experts suggest the model does not have an implicit definition of quality care, which makes it suitable to be applied to problems of broad or narrow scope. However, Donabedian notes that each of the three domains has merits and demerits that necessitate researchers to draw inferences and connections between them to create a chain of causation that is conceptually useful for understanding systems (2003). Coyle and Battles (1999) criticize the Donabedian model for failing to incorporate patient characteristics and environmental factors into the model. Coyle and battles stressed that these factors were vital to fully understanding the effectiveness of strategies employed during the care process. Patient factors such as genetics, socio-demographics, health habits, beliefs and attitudes, and preferences; and environmental factors such as patients' cultural, social, political, personal, and physical characteristics, as well as factors related to the ability of the care provider were all critical to patient outcomes (Coyle & Battles, 1999).

While there were other healthcare quality models or frameworks, the Donabedian Model remains the dominant paradigm for assessing the quality of health care (Swilling, 2020). The model addresses LOS, RR, and Cost of care as part of the structure, process, and outcome postulates of the model that relates to quality.

Nature of the Study

The nature of this study includes a descriptive correlational research design. The study used secondary data in the public domain on various hospitals in the Texas region. The Texas Hospital Data Collect website contains a database of 920 hospitals with healthcare information on the activities of various hospitals where the independent variables (LOS and RRs) - (IVs) and the dependent variable was Cost of care (C) - (DV).

Out of the 920 hospitals, 120 were targeted, with 84 randomly selected based on the selection criteria of accreditation and data on LOS, RR rate, Cost of care, and other relevant information to provide further insight into the study. The relevant data were stored securely on my password-protected laptop. Data analyses were performed using IBM SPSS 28 statistical software. Pearson's Correlation analysis was performed to examine whether any relationships exist between LOS – independent variable (IV), RR independent variable (IV), and C dependent variable (DV). A multiple regression analysis was performed to understand better if the Cost of care influences the relationship between LOS and RR. Understanding the correlations between the Cost of care and its relation to LOS and RR may reveal new insight into the study. This insight may help bridge the gap in knowledge for what was not known or well-understood about these relationships in hospitals and other places of care. Knowledge gap that results in discrepancies in reimbursement rates, policy decision-making, and, more especially, day-to-day patient care decision-making in the hospital.

Literature Search Strategy

This study intends to examine the relationship between inpatient length of stay, 30-day readmission rates, and cost of care in hospitals in Texas to provide insight into the financial implications for patients and third-party payers, including Medicare, Medicaid, uninsured, or private insurance. In addition, I examined if demographic factors of geographic region, age, year, gender, and race/ethnicity moderate the relationship between LOS, RR, and Cost of care among patients.

I extensively reviewed the variables (LOS, RR, and Cost of care) to conceptualize the study and provide adequate background information. I gathered relevant peer-reviewed sources from several online databases, including a thorough multi-database search, EBSCOhost, Academic Search Complete, government reports, Cochrane, PubMed, Google Scholar, and Cumulative Index to Nursing and Allied Health Literature (CINAHL). In addition, I researched additional related resources, including databases run by the Centers for Medicare & Medicaid (CMS) and the National Institute of Health (NIH). Finally, I included recent scholarship published within the last five years, and older relevant studies that were seminal were included as appropriate.

Little evidence in the literature supports the direct relational elements of all three keywords in the topic – *length of stay, 30-day readmission rates, and cost of care,* being studied collectively, especially within hospitals in Texas. Therefore, the search of peer-reviewed articles from several databases, including Google Scholar, Thoreau Multi-database Search, PubMed, EBSCO, and ProQuest, was performed using the keywords above individually and collectively. A search using these keywords yielded hundreds of thousands of articles. A more narrowed search delivered over 40,000 articles between 2016 and 2021. However, since this study aims to use articles that focus directly on the relationship of all three key phrases (Length of Stay, Readmission Rates, and Cost of Care), the articles for review were narrowed down to those relevant to the study. The following sections in this chapter provide an overview of the literature review strategies: an overview of the theoretical foundation that supports this research study and a more robust review of the literature related to key concepts and variables in the study.

Literature Review Related to Key Variables and Concepts

This study examined the relationship between Length of Stay, readmission Rates, and Cost of care using a descriptive correlational study approach. The study used secondary data from the Texas Department of State and Health Services (2018) hospital data collection. This literature review discussed the length of inpatient hospital stay, 30-day readmission rates, and cost of care in the healthcare setting and their implications to the patients, providers, and third-party payers.

Length of Stay (LOS)

Inpatient Length of Stay was one of the quality care metrics adopted by the CMS. Moreover, other quality improvement organizations have been defined as the number of days that a member stayed in an inpatient facility during a single episode of hospitalization (Vekaria, Overton, Wiśniowski, *et al.*, 2021). For example, according to the Agency for Healthcare Research and Quality (AHRQ, 2018), in 2016, there were about 35.7 million hospital stays with a mean length of stay of 4.6 days and a mean cost of $11,700 per stay. There were approximately 35.7 million hospital stays in the United States in that same year, representing a hospitalization rate of 104.2 stays per 1,000 population. Considering geographic differences in healthcare utilization and costs in the United States, the AHRQ, and other researchers have well-documented statistics. For example, the Healthcare Cost and Utilization Project (HCUP) Statistical Brief reported substantial differences in U.S. Hospital stays in 2012. The highest average hospital stays costs patients $12,300 compared to less than $11,000 in other regions (Kaiser Foundation, 2019). Factors such as differences in patient health status, treatment preferences, physician practice patterns, access to and availability of services, wages, and cost of living may help explain these types of geographic variation (Kaiser Foundation, 2018; Mallow, Belk, Topmiller, & Strassels, 2018).

The HCUP Statistical Brief also presented statistics on hospital inpatient stays in 2016, focusing on geographic variation based on the nine U.S. census divisions. The number and distribution of hospital stays were presented, along with the population rate, mean cost, and mean length of stay overall and by census division. For both the United States and each census division, the rate of stays was presented by unique patient characteristics such as age, sex, community-level income, and patient residence location, and the expected primary payer provides the distribution of stays.

Inpatient length of stay was calculated by subtracting the day of admission from the day of discharge. Ward, Patel, Elsaid, Jaisinghani, and Sharma (2021) reported that patients with an extended length of stay (LOS), often referred to as LOS outliers, posed a challenge to health systems by contributing to high care costs (C). In addition, such patients have a high probability of exposure to other risks associated with hospital-acquired conditions. LOS outliers were often associated with a high cost of care for the patient, paying out of pocket and insurance companies. Elsaid, Jaisinghani, and Sharma (2021) conducted a retroactive study involving LOS outliers and inliers. The results indicated that outliers stayed longer and cost more per stay than inliers. The takeaways from the study were (1) Length of stay (LOS) outliers who stayed greater than three standard deviations above the predicted LOS resulted in a median increased cost per stay; (2) hospital-acquired infections resulted in greater odds of becoming an LOS outlier; and (3) all LOS outliers had insurance coverage (Elsaid, Jaisinghani, & Sharma, 2021).

Bayer (n.d.) discussed the importance of LOS to patients, providers, and third-party payers. He noted that reducing hospital length of stay provides positive results for patients and financial benefits for the institution, especially when it is clinically viable. Bayer argued that in many cases, hospitals did not receive additional reimbursement when the patient's stay had passed the Geometric Mean Length of Stay (GMLOS) for their assigned Diagnostic Related Group. However, Bayer (n.d.) had some issues with calculating LOS among providers and suggested that LOS was calculated based on the CMS guidelines for GMLOS. GMLOS would become a discussion later in this section.

Yoneyama, Makita, Miyazu, Katsukawa, Yoneyama, Masuda, Nakajima, Kawasaki and Miyazu (2016) reported on the role of family variables on the length of stay of psychiatric patients in Japan. The study's objective was to investigate the association between family variables and the length of stay of patients with mental and behavioral disorders. The researchers examined the medical records of patients discharged within a year, except those discharged due to death were re-examined regarding age, laundry type, some family visits per month while hospitalized, and family structure before hospitalization. They considered a longer stay than six months as the cut-off point for an extended hospital stay. The results indicated that family washing was associated with shortened stays and frequency of family visits within a private psychiatric hospital in Japan. In contrast, family structure was not associated with these factors. This finding may support the criticism of Coyle and Battles (1999) of the Donabedian theory for ignoring patient characteristics in his model.

In another study, Wandella (2017) studied the length of stay and reimbursement rates for Medicare patients with chronic diseases. The researcher found that geographical adjustments and severity of medical diagnoses attributed to some dissimilarity in reimbursement rates and lack of financial consistency on the side of Medicare. Furthermore, the findings revealed that LOS and reimbursement rates for Medicare hypertensive patients had a significant correlation, and higher reimbursement rates were associated with longer hospital duration. These findings were essential to my research because issues resulting in financial problems for third-party payers and, eventually, providers were worth investigating. For providers, increased length of stay and readmission was often associated with poor quality, resulting in reimbursement problems, especially for Medicare. Wandella suggested that the source of more extended hospitalization and higher readmission rates among Medicare patients requires financial consistency or standardization, which Medicare has not realized for a while now.

Nishi, Maeda, and Babazono (2017) examined the impact of inter-provider care coordination on healthcare resource utilization among elderly acute stroke patients. They specifically looked at LOS and Total Charge (TC) concerning three care pathway groups: coordinated care, integrated care, and other pathways. The researchers found that compared with the other pathways, coordinated care had significantly shorter LOS of 2.0 days in acute ischemic stroke care; they had 2.5 days shorter LOS in hemorrhagic stroke care. However, they did not find significant differences in LOS and TC rehabilitation care. The findings suggested that a payment system for care coordination was inappropriate since it was not associated with reducing overall healthcare resource utilization. Nishi, Maeda, and Babazono (2017) recommended reforms to improve care continuity among multiple healthcare institutions in Japan due to resource utilization and cost disparity.

Geometric length of stay: Quality experts, regulatory bodies, and third-party payers have been concerned with patient LOS, as it impacts reimbursement rates and the quality of care. Providers were cautioned to stick to the Medicare geometric mean length of stay (GMLOS) for their assigned DRGs (CMS, 2021). Many healthcare providers have noted that the structure of the Medicaid benefit package was not the only factor influencing patient length of stay. There were characteristics such as patient population, the availability of alternative treatment settings, and the general level of overall demand for a facility that impacts LOS and must be considered (Judith & Frank, 1988). This argument was consistent with that of Coyle and battles (1999). Judith and Frank (1988) assumed length of stay was a function of four classes of variables: *LOS = fl..P, C, S, B),* (I) where P = patient characteristics that may influence the quality-quantity relationship, C = hospital characteristics that may influence the efficiency with which hospital services were produced, S = system variables that may facilitate hospital discharges, and B = the Medicaid benefit structure. The operationalization variables and their expected effect on LOS were among some of the concerns of Coyle and Battles.

Harmony Healthcare International (HHI) suggested that there were three ways to calculate LOS, namely, the average length of stay (ALOS), geometric mean (GLOS), and Median statistic (HHI, n.d.). HHI noted that using any of these calculation modes depends on the facility and the type of services they provide. However, they noted that the geometric mean was a precise representation of the central value in LOS calculation and was not as sensitive to outliers (HHI, n.d.). HHI advanced that from the formula below, for N number of patients, the geometric mean was the Nth root of the product of the individual patient days. However, the geometric mean calculation was simplified using natural logarithms, as shown below.

GMLOS = exp {(Ind1 +Ind2 + Ind3 + ……… Indn)/N}

There were some providers with other concerns regarding the actual calculation of LOS has stated that length of stay was generally calculated in days based on the patient's location and status at midnight (Hirsch, 2018). Hirsch (2018) argued that if a patient comes to the emergency department (ED) and checks in late on Monday night, gets an order for observation on Tuesday, is admitted as an inpatient on Wednesday, and then goes home on Friday. What should the LOS be? was it four days since the patient was physically in the hospital for four midnights, or was it three days since that first midnight was in the ED and did not count? Or was it two days since that was the number of inpatient days? These were questions that must be addressed. Hirsch further stated that if the length of stay was calculated based on inpatient days and he, as a doctor, wanted to make a length of stay good, he would put every patient in observation for a couple of days before agreeing to write an admission order. Hirsch argued that doctors' LOS numbers were tremendous in such cases but wondered what the cost and yardstick would be for LOS measurement. In agreement with other providers, Hirsch (2018) resolved that using the Medicare-published geometric mean length of stay (GMLOS) for every DRG must be the standard. However, Hirsch questioned the calculation used by the CMS. Hirsch recommended that such calculations be done from the claims data instead of its present form. Hirsch noted that an inpatient claim has data fields for admission date, start, and end of care, which were critical for calculating LOS (Hirsch, 2018). He further noted that the start of care would include any services provided in the three-day payment window, so if that date was used, it may artificially add days. Hirsch was concerned about the CMS calculation using the inpatient admission date. According to Hirsch, the inpatient admission date would not account for any hospital days spent when the patient was an outpatient receiving observation services. Using the GMLOS, he argued, would result in setting unrealistic goals. Under that aspect, an admission with one day of observation and two days of inpatient services would underestimate the length of stay by a third, driving doctors to hit an artificially low target (Hirsch, 2018).

Another critical point raised by Hirsch (2018) was the association of LOS with Cost of care. He argued that most LOS calculations did not correlate with Cost. In his argument concerning Cost, Hirsch advanced specific questions: was a doctor with a 4.8-day average length of stay and an average cost of $12,000 per admission better than the doctor with a LOS of 5.3 days and $10,000 per admission? He also questioned the idea of any hospital knowing the actual care costs for a single patient. Hirsch lamented that most calculations use adjusted charges based on the hospital's Medicare-designated charge-to-cost ratio. Hirsch (2018) concluded that using the Medicare-designated charge-to-cost ratio was an imprecise way to measure costs. Hirsch explained that LOS does not consider a payor source. He noted that if a payor pays a daily rate profitable for the hospital, physicians may discharge patients earlier and be paid. Hirsch also questioned adjustment to LOS based on patient acuity. This concern has been raised by Coyle and Battles (1999) when criticizing the Donabedian quality model. Hirsch (2018) mentioned that it only needs a few complex surgical patients assigned to a hospitalist to skew their

LOS number. Hirsch explained that hospitals often adjust for the case mix index (CMI). CMI, according to traditional healthcare, was a measure used by the CMS to determine hospital reimbursement rates for Medicare and Medicaid beneficiaries (Definitive healthcare, n.d.). The CMI accounts for the diversity, complexity, and severity of patient illnesses at a healthcare facility. A higher CMI denotes a hospital has treated a more significant number of complexes, resources-intensive patients, resulting in a higher reimbursement for the hospital. The opposite denotes low reimbursement for the hospital.

The CMS calculates the CMI by adding up the relative Medicare Severity. Diagnosis Related Group (MS – DRG) weight for each discharge and dividing that by the total number of Medicare and Medicaid discharges. Again, Hirsch questioned the validity of such a measure. He noted that the CMI was based on the assigned DRG.

Many experts noted that other factors affect patient acuity and cost, such as the social determinants of health, which were not considered in the DRG weighting (Hirsch, 2018; Coyle and Battles, 1999; Harmony Healthcare, n.d.; ACHE, 2021). Hospitals may assign a working DRG to each admission and expect the doctor to discharge the patients as the GMLOS approaches. Nevertheless, GMLOS was derived from hundreds of thousands of admissions and, as the title indicates, represents a mean length of stay (Hirsch, 2018). Hirsch noted that if a patient's stay exceeds the GMLOS, the doctor documents any comorbidities resulting in the admission with a higher-weight DRG and longer GMLOS or ensures documentation supports the patient's continued stay in the hospital. Hirsch warned that the doctor should not discharge or be asked to discharge the patient. If the doctor fails to discharge the patient as ordered by the administration or internal policy, he would be labeled an outlier or threatened with disciplinary action (Hirsch, 2018). Therefore, Hirsch contended that the actual relationship between the LOS and the Cost of care had been blurred. Many providers continue to seek ways of finding a balance and ensuring the actual value of LOS is obtained.

The average length of stay (ALOS): The average length of stay (ALOS) was the the most common statistic used by many industries to measure LOS (ACHE, 2021). The average was the mean of data taken over a given period. Mathematically, the ALOS becomes.

$$ALOS = (d1 + d2 + d3 + \ldots\ldots.\ dn)/N$$

Where $d1 + d2 + d3$ represents days in care, and N represents the total number of individual day events. ACHE (2021) noted that the ALOS calculation was biased when the LOS was positively skewed, resulting in outliers and a misleading assessment. Examples of outlier situations include a patient admitted for a day and then returning to the ER and patients who remain in a facility under Medicare for more than 80 days, to list a few (Hirsch, 2018; ACHE, 2021).

Bolin (2021) studied patients incubated in the Intensive Care Unit (ICU) to preserve their respiratory system. Specific exclusion criteria were created to determine if the patient was a candidate for early mobilization based on evidence-based practice methods. Outcome measures were the length of stay, length of intubation, VAP incidence rate, and length of enteral feeding infusion. After comparisons, results indicated statistically significant improvements in patients with an extended ICU stay and intubation length.

Avoiding length of stay outliers: One of the goals of any hospital is to avoid the length of stay outliers. Reducing inpatient length of stay impacts value and organizational performance and was linked with improving quality and access (American Hospital Association (AHA), n.d.). Shorter stays decreased a patient's risk of acquiring an infection and was a measurement of quality and good clinical practice. Managing length of stay increases inpatient capacity to meet growing demand, decreases complication rates, and supports the hospital's financial health. The Illinois Health and Hospital Association's annual Quality Excellence Achievement Awards were celebrated. The Integrated Healthcare Association (IHA) recognizes the achievements of hospitals and health systems in continually improving and transforming health care in the state (AHA, n.d.). Reducing hospital length of stays based on patient outcomes has been one of the ways healthcare institutions in Illinois were improving health and patient outcomes. In addition, the management of hospitals in Illinois strives to achieve the Triple Aim initiative introduced by the Institute of Healthcare Improvement (IHI) by improving the patient care experience.

Allen (2019) advanced that one of the ways to improve hospital financing was to reduce patient length of stays. Allen noted that since hospitals were paid based on DRGs, length of stay did not matter, which was a disadvantage when the patient stayed longer. The advantage here was that the quicker the patient was discharged, the sooner another patient was admitted. Allen (2019) suggested that the length of stay in days was a meaningless number and that the most important number was the length of stay index, which was given by:

Length of Stay Index = Length of Stay (Days)/Case Mix Index

Based on comorbid medical conditions, the case mix index adjusts for how sick the patient is (Allen, 2019). In other words, health insurance companies pay hospitals more if a patient has many comorbid medical conditions – Severity-Diagnosis Related Groups (MS-DRGs) rather than straight DRG.

The goal of providers, third-party payers, and the patient receiving care is to reduce patient LOS without impacting the quality of care. Many patients did not like being hospitalized and would prefer to receive treatment from home because of their proximity to family members and loved ones. Allen (2019) recommended that hospitals practice the strategy of reducing the length of stay and suggested ways to facilitate it. Some of the recommendations include: (1) increasing the case index, (2) adequate staffing of the hospital's case management department, (3) developing arrangements with high-performing skilled nursing facilities, (4) appropriately scheduling the operating room, (5) operate seven days a week, (6) making consultants co-managers, (7) consulting liberally, (8) start discharge plans on the day of admission, (9) practice multi-disciplinary rounds, (10) appoint guardians in a timely fashion, (11) elimination of emergency department boarding, (12) resizing of hospitalist staffing ratios, (13) resizing nurse staffing ratios, (14) continuously measuring the length of stay, (15) knowing with steps could be done as an outpatient, (16) using palliative care strategically, and (17) never admit patients at 11:59 pm.

Khosravizadeh et al. (2016) randomly examined patients' health records to show the influence of other factors on LOS. Using the Kolmogorov–Smirnov, Kruskal–Wallis, and Mann–Whitney U tests, results indicated that the mean hospital LOS, age, employment, marital status, history of the previous admission, patient condition at discharge, method of payment, and the type of treatment had a significant impact on LOS. Other factors, including gender, place of residence, and type of admission, did not affect LOS. Khosravizadeh et al. (2016) recommended that hospitals try limiting unnecessary LOS to reduce hospital costs. The authors also noted that LOS affects the cost and quality of provided care. Excessive hospitalization increases the use of limited resources and costs, while under-hospitalization causes unsatisfactory outcomes in treatment. Khosravizadeh et al. (2016) concluded that reducing the inappropriate stay of patients in a hospital decreases cost, improves hospital performance, reduces false bed occupancy rate, and increases hospital productivity.

Hospitals were under intense pressure from the CMS and other third-party payers to reduce patient LOS as long as it did not interfere with the quality of care. The Health Catalyst (2016) suggested that reducing LOS helps to reduce patient harm by avoiding unnecessary hospital-acquired conditions. In some cases, the longer the patient stays in the hospital, the higher the risk of acquiring hospital-acquired diseases.

As noted by Coyle and Battles (1999), the quality of care was determined by several factors, including patient characteristics, conditions of care, and other factors. Alwafi et al. (2021) conducted a retrospective cross-sectional study of COVID-19 patients and noted that patients had abnormal laboratory results, signs and symptoms. The researchers noted that patient characteristics of age and end-stage renal diseases significantly impact the mortality rate and the length of hospital stay among COVID-19 patients. The findings also showed that the escalated mortality rate and prolonged hospital stay were associated with older patients. These findings substantiated previous literature that LOS was impacted by other factors, including patient conditions (Wei et al., 2020).

Cedars et al. (2017) noted that LOS was the major the driver of inpatient care cost. The researchers analyzed the State Inpatient Databases from Arkansas, California, Florida, Hawaii, Nebraska, and New York. In patients with ACHD, hierarchical regression models were constructed to identify the clinical factors having the most significant effects on LOS. The Cleveland Clinic Orthopaedic Arthroplasty Group (2019) conducted a study to determine the influence of patient-related and structural-related risk factors as predictors of length of stay after total knee arthroplasty. The results indicated that patient-related factors such as older age, higher body mass index, higher Charlson Comorbidity index, and female sex were higher predictors of length of stay. The researchers concluded that despite patient-related factors providing substantial predictive value for the length of stay after knee arthroplasty, the main driving force of length of stay was structural-related factors like the hospital site and the caregiver.

Hospital managers should, therefore, develop a system for predicting LOS in order to save time and money. LOS has been shown to interfere with inpatient scheduling and admissions, resulting in financial losses for many hospitals. Ippolit et al. (2021) examined 16,000 hospitalizations using administrative data from hospitals' databases between January 2018 and December 2019. The authors assessed predictive models of hospitalization with a length of stays longer than recommended benchmarks. The results indicated that adopting current logistic predictive models reduced the length of stays by two days, guaranteeing 2,000 more hospitalizations in a year. With this change, hospital revenues have increased tremendously compared to previous times (Ippoliti, Falavigna, Zanelli, Bellini, & Numico, 2021).

In another research, Moyo, Doan, Yun, and Tshuna (2018) floated the idea of applying machine models used to predict the length of stay among healthcare workers to estimate the patient length. They suggested that if machine models were used to predict the length of stay, it might be possible to predict the patient's length using a similar methodology. Predicting patient length of stay would be a valuable tool to help providers plan effectively for patient census and other caregiving issues.

Readmission Rates (RR)

Hospital readmission was a significant quality parameter and part of healthcare reform in the United States. The current focus of the healthcare system, especially those of government systems like the CMS, in concert with other professional healthcare quality organizations, was to improve the quality of healthcare and patient outcomes. The CMS considers some of these readmissions preventable, hence the name “Potentially Preventable Hospital Readmission,” which was the return hospitalization within a set time that might have resulted from problems in care during a previous hospital stay or from deficiencies in a post-hospital discharge follow-up (CMS, 2021).

Emphasis was placed on reducing the 30-day readmission rates (Ostlling et al., 2017). Reducing readmissions benefited hospitals because providers were not reimbursed for patient stays beyond the required period or LOS.

The 30-day Readmission Rate requirement among care providers and regulatory bodies has become an important quality measure and a source for reducing healthcare costs (Rubin et al., 2017). The 30-day readmission measures include all unplanned readmissions within 30 days of discharge, regardless of the cause. The risk index includes patients readmitted to the same hospital or another acute care hospital for any reason, regardless of their primary diagnosis. The measures did not include planned readmissions. Currently, CMS measures hospital performance in the HRRP by calculating Excess Readmission Ratios (ERR) for each program measure. The institution of the Hospital Readmission Reduction Program (HRRP) was to determine the reimbursement rate for hospital readmissions for cases such as pneumonia, heart failure, chronic obstructive pulmonary disease exacerbation (COPD), acute myocardial infarction, and total hip/knee replacement (Ostlling et al., 2017). A hospital's ERR is the ratio of predicted-to-expected readmissions for a given measure (CMS, 2021). Hospitals with high ERRs were subject to a financial penalty. Many local, state, and national campaigns have emerged to help reduce readmission rates (Bradley et al., 2013). Despite increased attention to readmission issues, evidence regarding the best strategies for reducing readmissions was still limited (Bradley et al., 2013).

In a controlled trial study, readmission interventions included follow-ups and appropriate nurse staffing to demonstrate success (Coleman, Parry, Chalmers, & Min, 2006). However, Bradley et al. (2013) pointed out that less was known about the effectiveness of such interventions outside of controlled trials. However, significant variation exists in hospitals' strategies to reduce readmission (Bradley et al., 2012; House, Stephens, Whiteman, Biearman, & Printz, 2016).

Reducing hospital readmissions was a critical objective for hospital leaders. Readmission is a measure of quality and a CMS quality benchmark. It may result in high costs for healthcare delivery for both the federal government and hospitals, resulting in unnecessary increases in healthcare costs (Cox, Sadiraj, Schnier, & Sweeney, 2016). Although hospital readmissions have recently become a priority for CMS, the problem is not new (Warchol, Monestime, Mayer, & Chien, 2019). Readmission rates over the last several decades continued to increase until the recent interference of the Affordable Care Act through the HRRP program. The HRRP program aims to encourage hospitals to improve communication and care coordination that guarantees better patient and caregiver engagement in discharge plans and, in turn, reduces avoidable readmissions (CMS, 2021).

The CMS assesses a hospital's performance relative to other hospitals with a similar patient census, dually eligible for Medicare and Medicaid benefits as of 2019. As a result, the CMS included the following six procedure-specific 30-day risk-standardized unplanned readmission measures in the HRRP program: 1) Acute myocardial infarction (AMI), 2) Chronic obstructive pulmonary disease (COPD), 3) Heart failure (HF), 4) Pneumonia, 5) Coronary artery bypass graft (CABG) surgery, and 6) total hip arthroplasty and total knee arthroplasty (CMS, 2021).

Kripalani, Theobald, Anctil, and Vasilevskis (2014) reported that new financial penalties for institutions with high readmission rates had intensified efforts to reduce rehospitalization. Providers have employed creative ways to reduce RR, including patient needs assessment, medication reconciliation, patient education, arranging timely outpatient appointments, and providing telephone follow-up. These interventions have successfully reduced readmission rates for patients discharged home. However, the effect of interventions on readmission rates was related to the number of components implemented, whereas single-component interventions were unlikely to reduce readmissions significantly (Kripalani, Theobald, Anctil, & Vasilevskis, 2014).

Kapila (2016) conducted multiple case studies to explore organizational strategies leaders use to reduce readmission rates in hospitals in a non-Medicaid-expansion state. Kapila (2016) noted that using predictive analytics stratified by patient population was a key strategy to help reduce otherwise avoidable rehospitalizations. The study's findings suggested that leveraging data from electronic health records to identify at-risk patients provides comprehensive health information to reduce readmissions (Kapila, 2016). In the same study, Kapila (2016) indicated that hospital leaders also revealed that the need to understand and address the health needs of their local population, including social determinants such as lack of access to transportation and food and housing, were also critical in reducing readmissions.

The use of data analytics was a strategy to reduce readmission rates that have been documented as underused (Butler, 2018). Butler (2018) suggested that hospitals design an analytical model to predict the likelihood of patient readmission. The author further explained that the data collected from the model could be used to develop discharge protocols to prevent avoidable readmissions. Butler further explained that analytics could accurately predict readmission rates for patients with joint replacements. Butler also reported using data analytics to determine patients' probability of readmission, stratified by patient populations. Data analytics could improve clinical operations, monitor care patterns, and identify readmission risk.

Cost of Care (C)

The Cost of Care (C) was one of the most severe menaces of the U.S. healthcare system. Cost of care was often considered from the perspective of the providers, payers, and patients. From the provider's perspective, it was the expense incurred to deliver health care services to patients. It was the amount they pay to providers for services rendered to payers. To patients, it was the amount they pay out-of-pocket for health care services (Arora, Moriates, & Shah, 2015). Yang (2021) reported that the national per capita healthcare expenditures in the United States have increased significantly since 1960. Yang estimated the per capita healthcare expenditure of 2020 would be over $ 12,000. Compared to 1960, healthcare expenditures stood at 146 dollars (Yang, 2021). The dramatic increase in healthcare costs has been attributed to the high cost of prescription drugs and care. Rapoport, Fine, Manne-Goehler, Herzig, and Rowley (2021) conducted a cohort study of LOS, RR, and Cost of care charges during certain patients' hospitalization. The researchers discovered that the patients' cost of care was not adequately captured as some vital information was missing. For example, LOS was not captured as patients left the facility against medical advice. The authors also noted that in that specific study, readmissions in the cohort might have been undercounted in some instances, justifying the need for further studies to capture relevant results. Research findings were significant because they called for more reliable research where research variables were fully captured. Besides, the researchers would not recommend generalizing their results as further studies were needed to validate the study results.

In another study, Christensen, Spaulding, Pomputius, and Grapentine (2019) studied the effects of the care process on hospital LOS, RR, and cost of care based on treatments received by patients. The results showed that a decrease in the hospital-level average cost. Christensen et al. (2019) noted that the results were the same when hospital practice patterns were modeled using the average first day of service on which a patient received antibiotics orally. Furthermore, the authors noted that LOS and costs were not associated with a difference in 30-day readmission rates. The results were significant because the length of days and cost did not affect readmission, which was an interesting dynamic and needs to be explored (Christensen et al., 2019). Lee et al. (2019) also studied LOS, RR, Cost of care, onset, and mortality among heart failure patients. Again, the authors recommended further studies to uncover the underlying causes of the racial disparities among the patients and, more significantly, to help determine the role of cost, length of stay, and readmission in racial disparity.

Upadhyay, Stephenson, and Smith (2019) examined whether readmission rates affected hospital financial performance. Upadhyay et al. (2019) found that reduced readmission rates were related to increased operating revenues, as expenses associated with costly treatments related to unnecessary readmissions were avoided. Conversely, reduced readmission rates were related to an increase in operating expenses. Increased patient readmission rates may show a marginal increase in operating margin because of the higher operating revenues due to readmissions. The researchers recommended further studies using a larger dataset that includes data from more states and includes more periods to understand better the association between readmission rates and hospitals' financial performance. Generally, it was expected that increased readmission may result in more expenditures from third-party payers and patients but more income for hospitals. Upadhyay et al. (2019) noted that increased readmissions resulted in a gradual expense increase due to greater use of resources, which might lead to decreased profitability.

Zhang et al. (2019) examined the hospitalization costs caused by stroke and associated factors. The researchers found that factors significantly associated with costs were stroke types, insurance types, age, comorbidities, the severity of disease, length of stay, and hospital levels. The study highlighted the importance of the cost of care and the problems patients have in paying their hospital bills. Zang et al. noted that the nature of the disease condition and other comorbidities compounded these problems. This proposed investigation might provide an interesting point of comparison. In addition, it may help fill the gap in understanding by focusing specifically on the association between the variables. Either way, a significant positive or negative association has implications for quality and cost of care. Hospital Administrators should be alarmed at the overall patient quality outcomes, financial implications for all parties, and the accreditation status of their facilities when results point to poor quality.

Under the Affordable Care Act, readmission rates have become transparent, and hospitals are under financial stress for having excess readmission rates. Durand et al. (2020) used the Donabedian model to evaluate inpatient stroke care in a rehabilitation unit. Benchmarks for a length of rehabilitation stay (LoRS) were introduced based on median severity-specific loss care in the control group. The multidisciplinary team documented facilitators and obstacles affecting the prediction of patient benchmark attainment. Results indicated benchmarking the length of stay in rehabilitation reduced bed occupation and system costs without adversely affecting functional and sensorimotor patient outcomes.

In another study, Mallow et al. (2018) estimated the mean adjusted hospital costs, payments, and length of stay (LOS) for opioid-related patient visits. The eligible visits had a principal diagnosis of opioid use. Using separate regression models for inpatient and outpatient visits, the researchers estimated the adjusted costs, payments, and LOS for opioid-related visits. The results revealed that the adjusted mean cost and payment for an outpatient opioid-related visit varied across patients and regions. The variation was attributed to geographical and demographic characteristics and patient conditions. These variations in data based on the regional variation and national averages were necessary for hospitals to benchmark.

Zhang et al. (2019) examined the hospitalization costs by stroke and associated factors for inpatient costs. The researchers found that factors significantly associated with costs were stroke types, insurance types, age, comorbidities, the severity of disease, length of stay, and hospital levels. The study highlights the importance of the cost of care and the problems patients have in paying their hospital bills. Zang et al. noted that the nature of the disease condition and other comorbidities compounded these problems.

Healthcare costs continue to increase at an unsustainable rate in the United States, and inpatient hospitalizations, readmissions, and increased LOS were significant drivers of these costs. One of the ways the Utah hospitalists have identified to reduce the cost of inpatient care was to examine critical clinical decision support (CDS) (AACC.org, 2016). CDS involves activities like diagnostic tests. Yarbrough, Kukhareva, Horton, Edholm, and Kawamoto (2016) conducted a study to show that inappropriate laboratory tests contributed to healthcare waste. In a retrospective controlled interrupted time-series study, the authors evaluated the impact of a multifaceted laboratory reduction intervention on laboratory costs among patients 18 years or older admitted to the hospital to a service other than obstetrics, rehabilitation, or psychiatry. The measures included primary outcomes of lab cost per day and per visit, and the secondary outcomes were number of basic metabolic panel (BMP), comprehensive metabolic panel (CMP), complete blood count (CBC), and prothrombin time/international normalized ratio tests per day; length of stay (LOS); and 30-day readmissions. The results indicated that when the intervention group was compared to the control group, among the intervention group, the unadjusted mean cost per day was reduced after the intervention, and the unadjusted mean cost per visit followed the same trend. The ITS analysis also showed significant reductions in cost per day, per visit, and the number of BMP, CMP, and CBC tests daily. LOS was unchanged, and 30-day readmissions decreased in the intervention group. Yarbrough et al. (2016) concluded that a multifaceted approach to laboratory reduction demonstrated a significant reduction in laboratory cost per day, per visit, and common tests (Yarbrough et al., 2016).

In another study, Hersh (2016) noted that measuring outcomes was a multi-dimensional step and iterative process that should involve interdisciplinary teams at every step. Patient health outcomes were driven by structure and processes. Michelle, Lin, Blanchfield, Kakoza, Vaidya, Price, Goldner, Higgins, Lessenich, Laskowski, and Schuur (2017) evaluated a pilot quality improvement intervention to improve care coordination and reduce Emergency Department (ED) visits and hospitalizations among frequent ED users. The researchers pointed out that the average ED direct costs per patient were lower for inpatient direct costs for intervention patients compared with control patients. The study's results indicated that 1) the pilot randomized controlled intervention for ED care showed reduced ED visits, hospitalizations, and costs among intervention patients. 2) compared with control patients, patients enrolled in the program had fewer ED visits and fewer ED admissions, which were associated with a reduction in ED costs and inpatient costs. 3) Future efforts to reduce acute care utilization and costs in high-cost patient populations may benefit from engaging ED providers in identifying high-risk patients and coordinating care.

Jacobsmeyer (2020) highlighted three main points regarding patient care: 1) Recent changes to payment models along the continuum of care would facilitate the move to integrated care. Jacobsmeyer suggested that providers build strategic relationships across the healthcare continuum to achieve this goal and consistently provide cost-effective, high-quality care. Jacobsmeyer (2020) further noted that selecting the appropriate post-acute care partner can potentially improve outcomes and reduce the overall cost of care. 2) Jacobsmeyer (2020) advanced that inpatient rehabilitation was best equipped to handle complex patients because of the nature of their cases and staff training in these units. Inpatient rehabilitation was the only post-acute setting with the physician, nursing, and therapy coverage needed to serve the best medically complex patients who need physical rehabilitation. 3) Jocobsmeyer (2020) also suggested that adhering to quality benchmarks, regulations, and facility guidelines were additional ways to reduce LOS, RRs, and cost of care.

Although many studies have examined the financial relationships between health services delivery activities, this proposed investigation was the first to examine readmission rates, length of stay, and financial performance measures as quality patient outcomes in Texas. In addition, the study has implications for social change as findings would guide managers in strategizing ways to change health management practices to seek a balance between reducing readmission rates and maintaining profitability.

Definition of Terms

This section has definitions of terms to help provide clarity of meaning and better understand this study.

Length of Stay (LOS): Length of stay (LOS) means the number of days a member stayed in an inpatient facility during a single episode of hospitalization. Days of stay in a hospital as an inpatient were calculated by subtracting the day of admission from the day of discharge (Vekaria, Overton, Wiśniowski, *et al.*, 2021).

Readmission Rates (RR)/Preventable Readmission: Mayo Clinic defines hospital readmission as patient admission to a hospital within 30 days after being discharged from an earlier hospital stay. The standard benchmark the Centers for Medicare & Medicaid

Services (CMS) used was the 30-day readmission rate. Rates at the 80th percentile or lower were considered optimal by CMS (Mayo Clinic, n.d.).

Cost of Care/Cost Burden (C): Defined according to Merrian-Webster Dictionary (Merriam-Webster Incorporated, 2020) as the price paid for acquiring, producing, or maintaining something, usually measured in money, time, or energy; expense or expenditure; outlay suffering or sacrifice, loss, penalty. In this case, it is how much a patient pays for service-related care.

Inpatient Healthcare Utilization: Health Care Utilization refers to the use of healthcare services for many reasons, including preventing and curing health problems, promoting maintenance of health and well-being, or obtaining information about their health status and prognosis (Carrasquillo, 2013)

Reimbursement Rate: The Center for Medicare and Medicaid considers reimbursement rates the amount of money that Medicare pays doctors and other health care providers when they provide medical services to a Medicare beneficiary. Medicare also refers to the Medicare reimbursement rate as the Medicare Physician Fee Schedule (MPFS) (Center for Medicare & Medicaid, n.d.).

Cost of Hospitalization: To providers: the expense incurred to deliver health care services to patients. To payers: the amount they pay to providers for services rendered. To patients: the amount they pay out-of-pocket for health care services (Arora, V., Moriates, & Shah, 2015).

Premium. The fee paid for coverage of medical benefits for a defined period. Employers, unions, or employees can pay premiums or be shared by the enrollee and the plan sponsor (BLS, n.d.).

Health Insurance Claims: A health insurance claim is a request for payment of benefits for medical services provided to a beneficiary under the terms and conditions of the plan. The medical provider must file a claim before funds are reimbursed for qualified care provided (Healthinsurance.org)

Structure: Structure describes the context in which care was delivered, including hospital buildings, staff, financing, and equipment (Donabedian, 2003).

Process: Process denotes the transactions between patients and providers throughout the delivery of healthcare (Donabedian, 2003).

Outcome: Outcomes refer to the effects of healthcare on the health status of patients and populations (Donabedian, 2003).

Inpatient care. Includes institutional treatment in a hospital or specialized facility (BLS. n.d.)

Outpatient care. Includes treatment in one or more: outpatient hospital department, residential treatment center, organized outpatient clinic, day-night treatment center, and doctor's office. (BLS. n.d.)

Mortality Rate: A mortality rate measures the frequency of death in a defined population during a specified interval. (CDC, 2021).

Quantitative Research Design: Quantitative research design relates to the design of a research project that uses quantitative research methods. The design varies depending on the method used, such as telephone interviews, face-to-face interviews, online surveys, or surveys by post. Other methodologies include SMS / Test Message surveys or physical counts (Creswell & Creswell, 2018).

Correlation: Correlation means association. More precisely, it measures the extent to which two variables are related. There are three possible results of a correlational study: a positive correlation, a negative correlation, and no correlation. (McLeod, 2020)

Maximum out-of-pocket expense: The maximum amount a group member must pay out of pocket during a year. Until this maximum is met, the plan and group members share the cost of covered expenses. After reaching the maximum, the insurance carrier pays all covered expenses, often up to a lifetime maximum (Bureau of Labor Statistics, n.d.)

Excess readmission ratios (ERRs): A measure of a hospital's readmission performance compared to the national average for hospitalized patients with applicable conditions (CMS, 2017).

Healthcare Cost and Utilization Project (HCUP): A group of healthcare databases and related software tools and products developed through a federal and state industry partnership and sponsored by the Agency for Healthcare Research and Quality (CMS, 2021). The HCUP databases were a conglomerate of data collection efforts of state data organizations, hospital associations, private data organizations, and the federal government to create a national information resource of encounter-level healthcare data (CMS, 2021).

Assumptions

This quantitative study regarding the relationship between LOS, RR, and Cost and their financial implications was carried out with the following underlying assumptions:

1. Based on previous studies, there may be a correlation between length of Stay and readmission rates with financial implications for the provider, patient, and third-party payer (Wandella, 2017; Swelling, 2020).
2. The data used were valid and reflected actual patient information, and the data selected were randomized to give a broad representation of hospitals in Texas.
3. Patient information was collected under proper research conditions and was analyzed to produce usable data for inferences and further research.

Scope and Delimitations

The research problem in the study focuses on the relationships, if any, that exist between length of stay, readmission rates, and cost of care and to what degree. The goal was to understand better the financial implications posed by the interaction of these three variables on providers, patients, and third-party payers. The study used secondary data from the Texas Department of State and Health Services (2018) hospital data collection. Through the Texas Healthcare Information Collection (THIC), the Department of State and Health Services houses secondary data on patient readmissions, length of stay, and cost of care for different hospitals throughout Texas.

The study used data from a randomized selection of hospitals throughout Texas to allow for the generalization of research results. This randomized selection enhanced the credibility and trustworthiness of the results by providing an unbiased randomized sample size to represent a broader population of participating hospitals.

Although the intricacies of LOS, RR, and C have been largely unexplored, past studies grounded in the Donabedian theory have shown the influence of structure and structure on patient outcomes (Donabedian, 2013). Even though the focus of the study was specific to healthcare, applying these findings to other industries may result in beneficial use, including guiding individuals and third-party payers in their healthcare and financial decision-making.

Limitations

The study was limited to secondary data from the State of Texas Healthcare Information Collection (THIC), which houses data collected from various hospitals. In general, the government's published information was current and based on reliable research, even if no one author was listed (Austin Community College, n.d.). However, the need exists to be cognizant of problems that could arise when the information is vague and unreliable. If these limitations were ignored, the integrity of the research was tinted, and the findings may not help other organizations with decision-making. Although other moderating and mediating variables may influence LOS, RR, and C, those variables would not be considered in this study.

Significance

The United States has the highest healthcare cost per person compared to other nations (Statista Research Department, 2022). The annual health expenditures were estimated to exceed four trillion U.S. dollars in 2020, and the overall healthcare spending was estimated to be around 10,500 U.S. dollars per resident (Statista Research Department, 2021). Healthcare expenditures of this nature concern the patient, providers, third-party payers, and lawmakers. Any study addressing factors contributing to this increase, in part or whole, was significant and has implications for social change. Understanding how these different variables relate to our complex healthcare system would help bridge the gap in knowledge for healthcare workers, leaders, educators, patients, and researchers. In addition, it may provide information for individuals aiming to understand healthcare financing dynamics better. Finally, the study may help fill the gap in understanding by focusing specifically on the association between the variables. Either way, a significant positive or negative association has implications for quality and cost of care. Hospital Administrators should be 1) alarmed at the overall patient quality outcomes, 2) financial implications for all parties, and 3) regarding the accreditation status of their facilities when results point to poor quality. Under the Affordable Care Act, readmission rates have become transparent, and hospitals are under financial stress for having excess readmission rates.

Among studies that examine the quality and finance relationship within the healthcare field, this would be one of the first studies that examine the length of stay, readmission rates, and financial performance measures as outcomes among patient care in Texas. It has implications for social change as findings would guide managers in strategizing ways to change health management practices and provide insight into healthcare financing discipline, leadership practices, and the dynamic relation between

LOS, RR, and Cost of Care. It may also help to seek a balance between reducing readmission rates and maintaining profitability.

Summary and Conclusion

Chapter 1 of this proposed study provides background information on length Of Stay, Readmission Rates, and Cost burden or Cost of Care in hospitals in Texas. The chapter addresses the financial burdens and implications on the patients, providers, and third-party payers due to reduced or increased length of stay and readmissions (Upadhyay, Stephenson, & Smith, 2019; Wandella, 2017). The study was guided by two research questions investigating the relationship between LOS, RR, and Cost of care scores. In addition, a gap in the literature was established, revealing limited or no studies addressing the relationship that exists between LOS, RR, and Cost of care, specifically at hospitals in Texas, suggesting the need for further future studies Rapport, Fine, Manne-Goehler, Herzig & Rowley, 2021).

The study was presented with implications for future knowledge and social change. In addition, the knowledge gained from this study may help healthcare leaders, educators, patients, and researchers apply this insight to advance the healthcare field and make reliable decisions about care-related financing. Chapter 2 of this study provided a more thorough review of the literature associated with the nature and importance of Length of Stay, Readmission Rates, and Cost of Care to the patient, provider, and third-party payers. In addition, a thorough review of the theoretical framework of the Donabedian theory was provided in support of this study.

Section 2: Research Design and Data Collection

Introduction

Chapter 1 provided background to this study, a problem statement, and the study's purpose. Chapter 1 also provided formulated research questions and hypotheses the study aims to answer and test. Finally, a theoretical framework using Donabedian was presented, along with the nature and significance of the study. Key definitions relevant to the study were provided, and all assumptions and limitations were addressed accordingly.

Chapter 2 covered a comprehensive review of the literature and addressed the topics of the LOS, RR, and C, in addition to an in-depth review of the Donabedian theory and its application in healthcare practice. While the literature shares research on the length of stay, readmission rates, and cost of care, there exists a gap in knowledge around the relational elements of all three variables. A gap in understanding how the length of stay and readmission rates relate to the cost of care to the patient, provider, and third-party payers needs to be investigated. This study aims to conduct a quantitative analysis examining the relationship between the length of stay, readmission rates, and cost of care.

Research Design and Rationale

The variables being explored in the study were the length of stay, readmission rates, and cost of care. This study was a non-experimental descriptive correlational research design using secondary data. Health care and other hospital data were available for public use and accessed through the Texas Healthcare Information Collection Data website. Additional access or questions were directed through the (thcichelp@dshs.texas.gov or by calling (512) 776-7261). The secondary data consists of inpatient outcomes indicators used in hospitals' inpatient claims data to identify potential problem areas that could vary across hospitals and geographical areas. This data was readily available in the Texas Healthcare Information Collection Database for public use. In addition, demographic information was collected that includes the gender of the patients, age ranges, and gender. The statistical method was Pearson's correlation to test the correlations between length of stay, readmission rates, and cost of care. A multiple regression analysis was performed to understand whether the length of stay and readmission rates predicted the cost of care. These test results should answer the research questions and give further insight into the phenomenon under study. The study was provided, and all assumptions and limitations were addressed accordingly.

Methodology

Population

This study applied a quantitative descriptive correlational approach to examine the relationship between the length of stay, readmission rates, and Cost of care within hospitals. Secondary data from the Texas Department of State and Health Services (2018) was used. The Texas healthcare Information Collection Center collects all data regarding care provided in hospitals in Texas. The information was available at https://dshs.texas.gov/thcic. Through the Texas Department of State and Health Services, the Texas healthcare information collection center houses secondary data on patient readmissions, length of stay, Cost of care, and other viable care information for different hospitals throughout Texas from 2009 to 2018. Hospitals in the report were both psychiatric and acute care. Acute care hospitals provide surgical and medical care to patients needing immediate evaluation and treatment due to serious medical conditions.

I accessed the Texas Inpatient Hospital Data File for variables under study (readmission rates, length of stay, and Cost of care). The data was available in the public domain *and was easily accessible. I randomly selected hospitals with complete data for analysis. Those hospitals with incomplete data were discarded and replaced by hospitals with complete data relevant to the study.* Data on these variables was essential to my study because it provided data points for the dependent and independent variables to be analyzed and answer the research questions.

According to the County Office Organization (2021), there were 907 hospitals in Texas serves 27,419,612 people. Out of the database of 907 hospitals, 120 were targeted with specific attention to 84 randomly selected accredited hospitals. The inclusion criteria for participating hospitals were listed as (a) accredited hospitals and (b) must have enough data on inpatient LOS, RR, and Cost of care for acute myocardial infarction (AMI), pneumonia (PN), and heart failure (HF). Exclusion criteria included hospitals that did not have complete data on the variables under study and were not accredited by any government agency. However, 65 hospitals were finally selected as per G*Power analysis.

Sampling and Sampling Procedures

A G*Power software was used to calculate the sample size for the analysis and achieve a recommended level of confidence and power based on an anticipated effect size (Faul et al.,2014). Cohen's (1992) recommendation was used by setting the power to .80

and alpha to .05 to mitigate risk and balance the instances of Type I or II errors. Using a moderate effect size (Cohen, 1992), the format of a two-tailed correlation model on the G*Power software indicates that a sample size of 65 participants was needed for Pearson's correlation analysis. Using a multiple regression model on G*Power software with two predictors indicates that a sample size of 65 participants was needed. This study analyzed data from 65 hospitals to accommodate both analyses and answer the research questions, a sample well above the recommended samples given by Cohen (1992).

Instrumentation

I used secondary data in the study, which does not require research instruments. Access to the State of Texas Hospital Information Database was free and was readily available in the public domain. Participating hospitals were randomly selected and should have all the information needed to satisfy the research question. I specifically looked for information on hospital demographics, LOS, RR, and Cost of care for conditions under the same DRGs.

The SPSS 28 software efficiently conducted the Pearson correlation coefficient, multiple regression, and descriptive statistics. The software also helps to analyze large data sets to predict linear relationships between dependent and independent variables. The null hypothesis would be accepted or rejected based on inferences drawn from the data analysis.

Operationalization

Demographic data on hospitals was used to provide more insight into the study and consisted of the following: types of hospitals (acute and psychiatric presented as 1 –

acute and 2 - psychiatric) [nominal data]; ownerships (profit, nonprofit, and public – presented as 1 – profit, 2 – nonprofit, 3 - public) [nominal data]; Metro and Non-Metro status [nominal data presented as 1 – metro and 2 – non-metro status]; designations (Licensed status and non-licensed – presented as 1 – licensed and 2 – non-licensed) [nominal]; and bed count [ratio data – present in intervals].

The Texas hospital database presents the research variables in a structured data format, making it easy for the researcher to access, clean, and analyze.

The Cost of Care – was the dependent variable (DV) expressed in the average cost in [dollars – continuous data] for surgical procedures in the same DRGs in acute and psychiatric facilities. The cost of care for specific procedures was matched with the average LOS and RRs in these hospitals to establish the relationship between these variables.

Length of Stay – Independent Variable (IV) [continuous data] was measured by the amount of time spent in the hospital from admission to discharge (LOS = day of discharge – day of admission). LOS was converted to categorical data to facilitate further analysis, such as ANOVA and prediction analysis.

Readmission rates represent 30-day readmission rates [ratio data] measures evaluate what happens to patients once they leave the hospital after receiving care for certain conditions. The readmission rates focus on whether patients were admitted again at the hospital 30 days after being initially discharged. The readmission rates help make hospital comparisons accurate and meaningful for those hospitals treating sicker patients. The lower readmission rates were better for the hospital's performance.

I used secondary data, which differs from primary research, where participant's consent, use of research instruments, and a brief explanation of the study for participants were needed for ethical and other reasons. Therefore, the researcher meticulously used secondary data and scrutinized all data thoroughly to ensure the data were suitable and adequate for answering the research questions (Creswell, 2018).

Data Analysis Plan

Data analysis was done using IBM SPSS Statistical Software Version 28 (International Business Machines, 2017). Descriptive statistics was performed to assess and screen the data through the analyze/explore function in SPSS. Next, the data file was reviewed to determine missing data and issues of data normality, and appropriate measures were taken to ensure the data was useable, reliable, and valid for analysis. Hospital characteristics such as type of hospital, geographical location, number of beds, number of staff members, and length of time in operation in Texas were tabulated from the database and recorded.

The data analysis aims to answer the following research questions and hypotheses. The research questions and hypotheses formulated to guide the study were as follows:

RQ1: What was the relationship between the Cost of patient care (C) in Texas hospitals and Length of stay (LOS)?

*H*0: There was no significant relationship between the Cost of patient care (C) in Texas hospitals, length of stay (LOS).

*H*1: There was a significant relationship between the Cost of patient care (C) in Texas hospitals, and length of stay (LOS).

RQ2: What was the relationship between Cost of care (C) in Texas hospitals and readmission rates (RR)?

*H*0: There was no statistically significant relationship between the Cost of patient care (C) in Texas hospitals and readmission rates (RR).

*H*1: There was a statistically significant relationship between costs of patient care (C) and readmission rates (RR).

Several tests were conducted to answer research question one and its associated hypotheses, including demographic analysis, Analysis of Variance (NOVA), Pearson's Correlation, and multiple regression.

A *T*-test was used to determine if there was a significant difference between the means of the two groups and how they were related. T-tests were used when the data sets follow a normal distribution and have unknown variances. I did not conduct the *t-test* because the results were unnecessary to answer the research questions.

ANOVA test was used to compare three or more groups to gain information about the relationship between the dependent and independent variables. A one-way ANOVA has one categorical independent variable and a normally distributed continuous dependent variable. Sanders et al. (2016) used the ANOVA model to predict continuous outcomes based on categorical predictor variables.

Pearson's Correlation test was performed to examine the relationship between cost of care and length of stay and the strength of such a relationship to answer research question one. To answer research question two, I used the Pearson's Correlation test to determine the relationship between cost of care and readmission rates.

Multiple regression was conducted to examine the effects of LOS and RRs on the Cost of care. Specifically, the t-test in multiple regression was used to measure the difference in means between RR and LOS and how that impacts the Cost of Care while holding hospital characteristics as a control variable. The statistical confidence intervals were set at 95% and the significance level at ($P<0.05$) for all tests to help control for statistical validity.

The results of the tests were interpreted using descriptive statistics, tables, and charts to illustrate relationships between the variables and inferences drawn to explain the nature of the relationship and fully answer the research questions.

Threats to Validity

Validity assessments were necessary for research studies to ensure the instruments measure what they were designed to measure (Matthay & Glymour, 2020). Research data were usually assessed for validity, including external and internal validity. Understanding threats to validity provides alternative explanations for associations and other inferences that may be drawn from the data analysis. Since I used secondary data, I performed a test for validity for internal consistency.

External

Threats to external validity were related to how the study results were generalized to other populations outside the population under study. There were common concerns among healthcare workers and the general population concerning LOS, RR, and, more significantly, Cost of care (Swilling, 2020). A well-defined population for this study and a randomized unbiased sample helped minimize threats to external validity, making the study replication more generalizable to other healthcare organizations. Furthermore, the replication and generalization to other healthcare industries where inpatient LOS and RR result in Cost liabilities for the patient, the provider, and the third-party payer would matter. Such knowledge may help overall learning and improve processes.

Internal

Internal validity was essential in any research design to ensure the evidence in the study represents the relationship between the variables being studied. The study aims to investigate what relationships exist between variables and to what strength. In addition, to understand whether the Cost of care influences the relationship between LOS and RR. The word relationship was used consistently, and careful attention was given to the randomization of participating hospitals in the selection process to avoid bias and reduce internal threats. Truelifevurtue (n.d.) outlined the nine most significant threats to validity: history events, maturation, confounding variables, attrition, repeated testing, instrumentation, statistical regression and conclusion, diffusion, and explanation bias. Threats that were directly related to this study were discussed below.

Reliable data should be accurate and complete. The reliability of secondary data was tested by finding out several things about the data, including: (1) Who collected the data? (2) What were the sources of data? (3) Were they collected using proper methods? (4) At what time were they collected? (5) Was there any bias in the compiler? (6) What level of accuracy was desired? (7) Was it achieved? (Oluwaseun, Olateju, & Bakare, 2019).

Data from the Texas Department of Health Services Hospital Data Collection database was considered a government data source and reliable and valid (Creswell, 2018). The need to use relevant data in research cannot be underestimated. Data suitable for one inquiry may not necessarily be found suitable in another. Therefore, it should not be used if data is unsuitable for any investigation. Similarly, the original inquiry's object, scope, and nature must also be studied. If the researcher finds differences in these, the data remains unsuitable for the present inquiry and should not be used (Human.texts.org, 2019). I scrutinized the data for suitability, primarily to ensure the research questions were addressed appropriately.

The adequacy of the data was also another essential aspect of its usability in secondary research. If the accuracy of the data was found inadequate for the research, the research should not use the data (Creswell, 2018). In addition, the data would be considered inadequate if they were very narrow or failed to address all areas of the research questions. It would be hazardous and may result in an unreliable outcome. Available data should be reliable and adequate (Creswell, 2018). However, the researcher should not mindlessly discard such data if they were readily available from authentic sources and suitable and adequate. I relied on the original reliability and validity of the data collection and preparation procedures since they were obtained from government sources.

Data reliability and validity were crucial elements of this research. There were various forms of reliability, including (1) Inter-Rater or Observer reliability, the degree to which different raters or observers give the same responses. (2) Test-Retest Reliability refers to the consistency with which the instrument measures test items. (3) Parallel - Forms reliability measures the reliability of two tests of a similar construct. (4) Internal consistency reliability refers to the consistency to which the instrument measures what it was designed to measure and was measured as Cronbach's Alpha. Since I used secondary data, the measure of internal consistency does not apply here.

Statistical Regression and Conclusion

To mitigate threats to statistical regression and conclusion, I ensured a full assessment of the statistical methods chosen to perform the analysis, and all assumptions for the methods were met. The statistical confidence intervals were 95%, and the significance level was $\alpha = .05$ to help control for statistical validity (Long & Godfrey, 2004). The sample was adequate as per G *power analysis to ensure the viability of the study.

Construct

I relied on the construct validity as accounted for by government researchers who prepared research instruments to collect the primary data. I hoped all risks were mitigated by ensuring survey items were clear and the use of common language did not require participants and participating hospitals to have a broad understanding of the topics. I believed that the questions were simple and easy to follow. I hoped that the informed consent to participants ensured confidentiality was upheld per ethical guidelines and respect for participants.

Ethical Procedure

Ethical issues were thoroughly considered and observed throughout the research process. There were fundamental issues related to secondary data use and analysis, especially with the advent of technology. Data sharing, compiling, and storage have become much easier, but there were also data confidentiality and security issues, especially the use and transfer of patient data. The basic concerns about the secondary use of data were mostly around potential harm to individual subjects. However, secondary data vary in the amount of identifying information in it. The dataset used in this study did not have identifying information, implying that a full review by the ethics board was unnecessary as it posed no potential harm to the participants. Ethical consideration procedures involving participants do not present a problem here because the data proposed data was in the public domain. However, the research proposal was presented to the Institutional Review Board of Walden University for approval, which was not a problem since the research does not physically involve human subjects. The participating hospital did not need approval regarding compliance issues since the data was in the public domain. However, further ethical considerations were made regarding data analysis and reporting.

Summary

This study aimed to apply a quantitative descriptive correlational approach to investigate the relationship between LOS, RR, and Cost of care within a hospital environment. A non-experimental Pearson's correlation method was used to test the relationships between all variables. Then, multiple regression analysis was performed to understand whether the Cost of care influences the relationship between LOS and RR. Secondary data obtained from the Texas department of Health Hospital Data Collection database was used provided they meet all inclusion criteria outlined for the study.

I gave careful attention to reducing threats of validity. Session 3 displayed and interpreted the results and findings from the study. Furthermore, I addressed any implications for practice, research of the study, and advance recommendations for additional research in session 4.

Section 3: Presentation of Results and Findings

Introduction

The purpose of this quantitative study was to investigate the financial implications of Length of Stay (LOS) and Readmission Rates (RR) on the Cost of Patient Care (C) in Texas, United States. The main research questions and hypotheses for the investigation were:

RQ1: What was the relationship between the Cost of patient care (C) in Texas hospitals and Length of stay (LOS)?

*H*0: There was no significant relationship between the Cost of patient care (C) in Texas hospitals, length of stay (LOS).

*H*1: There was a significant relationship between the Cost of patient care (C) in Texas hospitals, and length of stay (LOS).

RQ2: What was the relationship between Cost of care (C) in Texas hospitals and readmission rates (RR)?

*H*0: There was no statistically significant relationship between the Cost of patient care (C) in Texas hospitals and readmission rates (RR).

*H*1: There was a statistically significant relationship between costs of patient care (C) and readmission rates (RR).

The data analysis process was performed using SPSS version 28. The data were mined from the Texas Health Data website, which contains the Texas Health Care Information Collection (THCIC) on hospital inpatient data. The following section describes how the sample size was obtained, demographic data analyses, inferential data analyses, interpretation of the findings, study limitations, recommendations, and implications for social change and future research.

G*Power Analysis

A G*Power analysis was conducted to determine the appropriate sample size for the data analysis process. Determining power was important in research to minimize the risk of committing Type 2 errors when judging the population effect. Therefore, using the right sample size was important to avoid making Type II errors when interpreting the results. In the context of the present study, the researcher estimated the necessary sample size to test the R-square at an alpha level of .05 for a multiple regression model entailing two predictors (Length of Stay and Readmission Rates) on one outcome variable (Cost). For the analysis, the desired power for the test was .99, and the projected population R-Square was .26, corresponding to a large effect size of $f^2 = .35$ (See Figure 1 & Table 1). According to Cohen (1992), .80 was a conventional standard for general use when conducting a power analysis. The researcher raised the value to .99, which complements a .01 error rate of Type II error. Conceptually, the setting means that the probability of the researcher correctly rejecting a false null hypothesis was 99%, whereas the probability of failing to reject a false null hypothesis correctly was 1%. The G*Power Analysis above shows that given the conditions described above, the most appropriate sample size for the following analysis was 65 hospitals from Texas. Therefore, a random sample of 65 hospitals was selected from the Texas Hospital Inpatient Use dataset for the analysis in this research.

Figure 2

*G*Power Analysis*

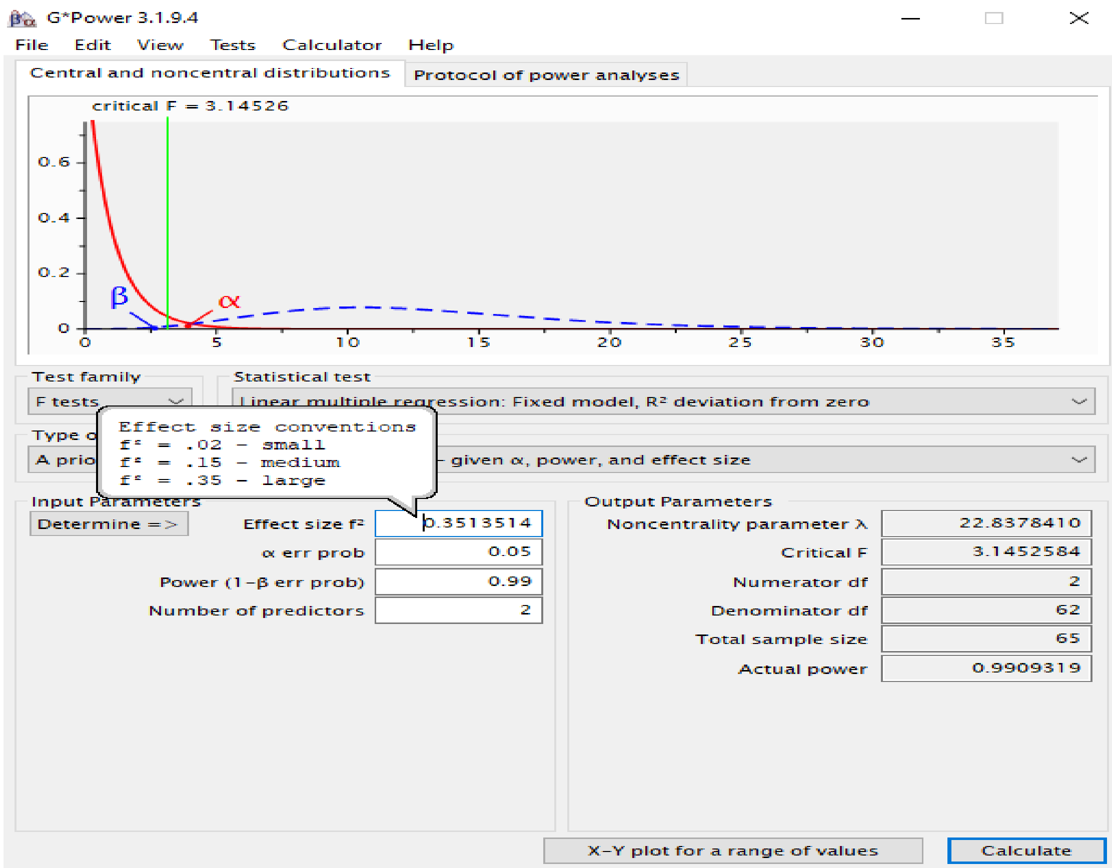


Table 1

Results of the G Power Analysis*

G*Power Analysis Results		
Input: Effect size f^2	=	0.3513514
α err prob	=	0.05
Power (1-β err prob)	=	0.99
Number of predictors	=	2
Output: Noncentrality parameter λ	=	22.8378410
Critical F	=	3.1452584
Numerator df	=	2
Denominator df	=	62
Total sample size	=	65
Actual power =		0.9909319

F tests - Linear multiple regression: Fixed model, R^2 deviation from zero
Analysis: A priori: Compute required sample size

Demographic Data Analysis

Demographic data analysis was performed to understand the different characteristics of the dataset. The initial demographic characteristic investigated was to understand the ownership of the hospitals. The hospital ownership was categorized into for-profit, non-profit, and public. The findings are depicted in Table 2 below. The descriptive statistics show that 52.3% of the hospitals in the sample were for-profit, 22% were non-profit, and 9% were public (See Table 2).

Table 2

Hospital Ownership in Texas

Ownership				
	Frequency	Percent	Valid Percent	Cum. Percent
For-Profit	34	52.3	52.3	52.3
Non-profit	22	33.8	33.8	86.2
Public	9	13.8	13.8	100.0
Total	65	100.0	100.0	

The descriptive statistics also sought to evaluate the metro status of the hospitals in Texas State. The hospitals were categorized into metro and non-metro hospitals. The findings show that most hospitals in Texas (78.5%) were in metro regions, while fewer (21.5%) of the hospitals were in non-metro regions (See Table 2). In addition, the researcher evaluated the license type of the selected hospitals. The researcher was interested in acute care hospitals only.

Therefore, all the hospitals included in the dataset were acute license-type hospitals (Table 3).

Table 3

Hospital Metro Status and Licensed Type

Metro Status				
	Frequency	Percent	Valid Percent	Cum. Percent
Metro	51	78.5	78.5	78.5
Non-Metro	14	21.5	21.5	100.0
Total	65	100.0	100	
Licensed Type	65	100.0		

Furthermore, the researcher captured the procedure groups for which data about the length of stay, readmission rate, and cost of care were considered in this research. There were eight procedure groups investigated, including abdominal paracentesis (41.5%), alcohol and drug rehabilitation (18.5%), amputation of the lower extremity (4.6%), arthroplasty knee (18.5%), blood transfusion (10.8%), cancer chemotherapy (1.5%), cesarean section (3.1%), and other vascular catheterization (not heart) (1.5%) (See Table 4).

Table 1

Procedural Group for Texas Hospitals

Procedures		**Procedural Groups**		
	Frequency	%	Valid %	Cumulative %
1. Ab	27	41.5	41.5	41.5
2. Adr	12	18.5	18.5	60.0
3. Ale	3	4.6	4.6	64.6
4. Ak	12	18.5	18.5	83.1
5. Bt	7	10.8	10.8	93.8
6. Cc	1	1.5	1.5	95.4
7. Cs	2	3.1	3.1	98.5
8. Ovc	1	1.5	1.5	100.0
Total	65	100	100	

Ab = Abdominal paracentesis; Adr = Alcohol/Drug Rehab; Ale = Amputation of lower extremity
Ak = Arthroplasty Knee; Bt = Blood Transfusion; Cc = Cancer Chemotherapy; Cs = Caesarean section; Ovc = Other Vascular Catherization

The researcher evaluated the patient status of the individuals whose data was captured in the dataset. The patient status categories were transferred to another type of health care institution not defined elsewhere in the code list, discharged to home or self-care routine, or transferred to home under the care of an organized home health service organization. The analysis findings show that 1.5% of the patients were transferred to another type of health care institution not defined elsewhere in the code list, 95.4% were discharged to home or self-care, and 3.1% were transferred to home under the care of an organized home health service organization (See Table 5).

Table 2

Patient Status of the Participants

	Patient Status			
	Frequency	%	Valid %	Cum. %
D/T o CF	1	1.5	1.5	1.5
D/T o HSC	65.2	94.5	95.4	96.9
D/T o OHC	2	3.1	3.1	100.0
Total	65	100.0	100.0	

D/T o CF = Discharged/Transferred to another care facility
D/T o HSC = Discharged to home or self-care
D/T o OHC = Discharged or transferred to home under the care of an organized home care

Data Analysis and Presentation of the Results

The researcher investigated regression analysis assumptions and determined that the key variables fulfilled all the relevant assumptions. The first set of analyses focused on the correlation between the variables. The second set of data analysis focused on constructing a linear regression model to evaluate the relationship between the independent and dependent variables.

Correlation Between LOS and C

The researcher conducted an analysis exploring the relationship between length of stay and cost of care in acute care hospitals in Texas State. The analysis helped answer the first research question: What was the relationship between the cost of patient care in Texas hospitals and length of stay? Pearson's correlation was used to examine the relationship. The statistical analysis findings are given in Table 9. The correlation analysis shows that the mean average length of stay was 4.81 days (*SD* = 2.869 days). On the other hand, the mean average total charges were $60,347.3471 (*SD* = $70,637.885) (See Table 9). The analysis findings show a significant negative relationship between average length of stay and average total charges or cost, with Spearman's rho, $r = -.291$, $p = .019$ at the .05 alpha level (See Table 6, Correlations).

Table 3

Correlation Between Cost of Care and Length of Stay

	Correlation		
Rho		1	2
	Avg. LoS	1.000	- .291*
	Avg. TC	- .291*	1.000

**Correlation significant at the 0.05 level (2-tailed); Avg. LoS; Avg. TC*

Correlation Between RR and C

Further correlation analysis evaluated the relationship between the readmission rate or number of inpatient hospitalizations and the average total charges or cost of care. The descriptive statistics showed that the mean total charges were $60,347.347 (*SD* = $70,637.885) (See Table 10, descriptive statistics). On the other hand, the average readmission rate was 29.95 days (*SD* = 53.119 days) (See Table 10, descriptive statistics). The analysis findings show no statistically significant relationship between the average total charges (cost) and the readmission rate, Spearman's rho, $r = .067$, $p = .594$ (See Table 7, correlations).

Table 4

Correlations Between Cost of Care and Readmission Rate

	Correlation		
Rho		1	2
	RR	1.000	.067
	Avg. TC	.067	1.000

**Correlation significant at the 0.05 level (2-tailed)*
RR = Readmission Rates
Avg. TC = Average Total Cost

Multiple Regression Analysis for LOS, RR, and C

A multiple regression analysis was tested to understand the relationship between length of stay, readmission rate, and the cost of care. The regression model summary shows that the adjusted R-Square for the relationship was .018, which depicts the effect size (See Table 11, Model Summary). Therefore, the R-Square value shows that the two predictors could explain 1.8% of the variation in the dependent variable. The ANOVA model shows that the regression model was not statistically significant, F (2,62) = 1.591, p = .212 (See Table 8, Regression Analysis). Therefore, there was no need to interpret the coefficients because the regression model was not statistically significant. In other words, Average Length of Stay and Average Readmission Rates did not predict Cost of Care in this study.

Table 5

Regression Analysis

Model Summary

R	R^2	*Adjusted* R^2	*Std. EE*	*Durbin-Watson*
.221[a]	.049	.018	69993.97	1.993

a. Predictors: (Constant), Number of inpatient hospital Readmission Rate, Avg. Length of Stay
b. Dependent Variable: Average Total Charges ($)
Std.EE = Standard Error of Estimate

ANOVA

Model	*SS*	*df*	*Mean Square*	*F*	*Sig*
Regression	155	2	779	1.591	.212[b]
Residual	3.03E+11	62	489		
Total	3.193E+11	64			

a. Dependent Variable: Average Total Charges ($)
b. Predictors: (Constant), Number of inpatient hospital Readmission Rate, Avg. Length of Stay

Coefficient[a]

Model	**USB**	**CSE**	**SCEB**	***t***	**Sig**	**Upper**	**Lower**	**CT**	**SVIF**
Constant	845	183		4.59	<.001	477	121		
Avg. LoS	-528	307	-.215	-1.719	.091	-114	860		
Avg. RR	42.64	166.0	.032	.257	.789	-289	374.55	.984	1.016

a. Dependent Variable: Average Total Charges ($)

Summary and Conclusion

Descriptive data analysis of the demographic data was performed to understand the dataset's characteristics before performing inferential analysis. Demographic data analysis shows most hospitals in Texas were for-profit, followed by non-profit, and finally public. Hospital metro status data revealed that more hospitals were located in metro regions than non-metro. All hospitals used in the analysis were acute license types and performed different procedures. The patient status showed most participants were discharged to home or self-care routine. Inferential analysis shows there was no correlation between total cost and hospital readmissions. The data analysis revealed a significant correlation between the average length of stay and total cost. The linear regression model was not statistically significant. Therefore, there was a need to explore other factors that predict the cost of healthcare in Texas.

Section 4: Application to Professional Practice and Implications for Social Change

Introduction

The general purpose of this quantitative study was to examine the relationship between Cost of Care, length of Stay, and Readmission Rates among hospitals in Texas. Secondary data was obtained from the Texas Hospital Database and subjected to analysis. A quantitative descriptive correlational approach was right for this study to reveal the relationship between Cost of Care (Dependent variable), LOS, and RRs (Independent variables). Concern for the rising cost of care and subsequent patient and third-party obligations triggered the study. I collected secondary data from the public domain from the Texas Hospital Data Collection database and subjected it to analysis using SPSS 28 Statistical Software. The following section covers the interpretation of the findings, study limitations, recommendations, implications for professional practice and social change.

Interpretation of Findings

Results for research question one tested with Spearman's Correlation analysis revealed a significant negative relationship between average length of stay (LOS) and average total charges or cost (C). The results align with findings by Wandella (2017), who established that LOS impacted the cost of healthcare, with longer stays attracting higher healthcare costs. In another study, Nishi, Maeda, and Babazono (2017) found that shorter hospital stay was associated with lower healthcare costs than longer. Cedars, Benjamin, Burns, Novak, and Amin (2017) agree with the findings in this study, Wandella (2017), and Nishi et al. (2017) that length of stay is a significant predictor of the cost of healthcare. According to Cedars et al. (2017), length of stay is a major driver of healthcare costs despite patient factors, such as age, condition, and gender, playing a major influential role. Thus, the relationship between the average length of stay and the average total charges or cost in healthcare settings could vary and was influenced by various factors (Cedars et al., 2017). Therefore, the findings in this study align with previous studies that as the average length of stay increases, the average total charges or cost may also increase, and vice versa.

This study noted a notable observation about the relationship between LOS and C. The findings showed that there is a negative correlation between the two variables. The rationale behind this potential negative correlation was that a longer stay in a healthcare facility typically involves more resources, such as medical staff time, medications, procedures, and other services. These additional resources contribute to higher costs, which are then reflected in the total charges or bills for the patient's care. Conversely, the average length of stay may decrease when hospitals and healthcare facilities implement strategies to streamline patient care, improve efficiency, and reduce unnecessary delays. The result could lead to lower resource utilization and subsequently lower total charges or costs for patients. It's important to note that this correlation was not always straightforward, and there were cases where other factors might influence the relationship. Some factors that could affect the relationship between average length of stay and average total charges or cost include:

1. Severity of Illness: Patients with more severe medical conditions might require longer stays and incur higher costs due to the complexity of their care.

2. Medical Procedures: Certain procedures or treatments could significantly impact the length of stay and costs. Complex surgeries or specialized treatments may lead to longer stays and higher costs.
3. Hospital Policies: Hospital policies, insurance coverage, and reimbursement structures could also play a role in determining the final charges and costs.
4. Efficiency Measures: Hospitals with efficient care pathways and discharge processes could potentially reduce the length of stay without compromising patient outcomes, reducing costs.
5. Case Mix: The mix of patients and their conditions in a hospital could influence the average length of stay and costs.
6. Geographic Variability: Healthcare costs and length of stay could vary widely based on geographic location and local healthcare market dynamics.

To better understand the specific correlation between average length of stay and average total charges or cost, it's important to analyze data from relevant healthcare settings and studies. The negative correlation finding agreed with Ippoliti et al. (2021), who observed that healthcare costs depend on a range of factors, which might influence its relationship with key predictors, such as LOS. Similarly, Moyo et al. (2018) agree with Ippolity et al. (2021) and the findings in this study by observing that a range of factors can impact the relationship between LOS and C in healthcare.

To answer research question two, Spearman's *Rho* Correlations showed that the absence of a clear relationship between the average cost of care and average readmission rates in healthcare settings could be influenced by various factors. It's important to recognize that healthcare is a complex system with many variables that could interact differently. Here are some possible causes for the lack of a relationship between these two variables:

1. Quality of Care: Hospitals prioritizing high-quality care might have higher costs due to the resources and expertise required to provide comprehensive treatment. However, this focus on quality care could lead to better patient outcomes and lower readmission rates, potentially counteracting any direct correlation between costs and readmissions.
2. Preventive Care: Hospitals that invest in preventive measures, patient education, and early interventions may have higher costs upfront. However, these measures could help reduce the likelihood of readmissions and overall healthcare costs over time.
3. Effective Discharge Planning: Hospitals emphasizing thorough discharge planning and post-discharge care coordination may incur higher costs due to extended care services. However, these efforts could lead to better patient recovery and reduced readmission rates.
4. Population Demographics: Hospitals serving diverse patient populations may encounter varying healthcare needs and social determinants of health.

These factors could impact costs and readmission rates, potentially obscuring a direct correlation.

5. Outpatient Services: Hospitals with strong outpatient services and follow-up care might have higher costs associated with ongoing patient management. However, this could lead to better post-discharge outcomes and reduced readmissions.

6. Regional Variability: Healthcare practices, local resources, and socioeconomic factors could vary by region, influencing the relationship between cost and readmission rates.

7. Healthcare Policies: Changes in healthcare policies, insurance coverage, and reimbursement structures could affect how hospitals allocate resources and manage care, impacting the relationship between costs and readmissions.

8. Data Accuracy and Measurement: Variations in data collection methods, coding practices, and measurement techniques could affect how costs and readmission rates were calculated and might obscure a relationship that could exist.

9. Time Lag: The impact of cost-saving initiatives or quality improvement efforts might not be immediately reflected in readmission rates. It could take time for these changes to result in noticeable reductions in readmissions.

10. Patient Adherence: Factors related to patient adherence, such as medication compliance and lifestyle changes, could significantly affect readmission rates, potentially overshadowing any direct correlation with costs.

11. Risk Stratification: Hospitals that effectively identify and manage high-risk patients might have higher costs associated with targeted interventions. However, these efforts could lead to lower readmission rates among this subgroup of patients.

The absence of a clear relationship between the average cost of care and average readmission rates does not necessarily indicate inefficiency or lack of effectiveness. It was essential to consider the broader context, including the quality of care, patient outcomes, and the various strategies employed by healthcare facilities to improve patient care and reduce readmissions. Furthermore, third-party payers were reluctant to pay for unnecessary readmissions, especially for repeat conditions. Previous research highlights that healthcare organizations set up different strategies to curb healthcare costs, which may impact the measurement of the relationship between RR and C. For instance, Warchol et al. (2019) indicated that hospitals use different strategies to keep their readmissions low to avoid negative consequences from the CMS. Financial penalties imposed by the CMS on hospitals with high readmission rates force hospitals to avoid readmission rates (Kripalani et al., 2014). Many hospitals develop discharge strategies or protocols that prevent avoidable readmissions (Butler, 2018). As such, the cumulation of these factors may contribute to the absence of a significant relationship between RR and C.

The multiple regression analysis test results revealed no significant relationship between length of stay, readmission rate, and the cost of care in this study. The relationship between the variables was not linear, so there were no predictive properties displayed among the variables. That is, length of stay and readmission rates did not predict the cost of care in this study. Length of stay and readmission rates did not necessarily predict the cost of care as it often depends on the context, healthcare setting, and patient population. Here are some points to consider supporting this perspective:

1. Variability in Patient Conditions: Patients have diverse medical conditions and complexities that could impact their length of stay and readmission rates. More severe or complicated conditions might lead to longer stays or a higher likelihood of readmission, but this doesn't always directly correlate with increased costs.
2. Quality of Care: Hospitals and healthcare systems that provide high-quality care might achieve shorter lengths of stay and lower readmission rates due to effective treatments and interventions. However, the cost of this care might be higher due to the utilization of advanced technologies, specialized staff, and better resources.
3. Care Coordination and Management: Effective care coordination, discharge planning, and outpatient follow-up could reduce readmissions and length of stay. While these measures were important for patient

outcomes, they might not necessarily lead to lower costs, as they require additional resources for coordination and support.

4. Value-Based Care: In value-based care models, healthcare providers were incentivized to improve patient outcomes while reducing costs. The models could lead to scenarios where lower readmission rates and shorter lengths of stay were achieved; but the upfront investments in care management might result in similar or even higher costs.
5. Population Health Factors: Socioeconomic factors, patient demographics, and access to outpatient care could influence readmission rates and lengths of stay. These factors could be independent of the actual cost of care delivery.
6. Data and Analysis Limitations: The relationship between these factors and costs might not be linear or direct due to data limitations, variations in cost calculation methodologies, and other confounding variables.
7. Complex Healthcare System: Healthcare costs were influenced by multiple factors, including administrative overhead, pricing negotiations, billing practices, and regulatory requirements. These factors could override the direct impact of length of stay and readmission rates on costs.

It was important to emphasize that healthcare economics is multifaceted, and simplistic correlations might not always capture the intricate relationship between patient outcomes and costs. Although the cost of care in the United States is rising, the independent variables, RR and LOS, did not significantly predict cost. The findings align with Christensen et al.'s (2019) study, which noted that LOS and costs were not associated with 30-day readmission rates. Similarly, Lee et al. (2019) failed to establish a significant relationship between LOS, RR, and C for patients with heart failure. Lee et al. recommended further research on the mediating and moderating factors influencing the relationship between LOS, RR, and C. However, other studies, such as Upadhyay et al. (2019), showed that readmission rates impacted hospitals' financial performance. Zhang et al. (2019) acknowledged that while LOS and RR may impact C, additional factors play a significant role in the relationship for stroke patients, such as type of stroke, insurance type, age, severity of the disease, comorbidities, and hospital level. Therefore, a range of mediating factors influence the relationship between LOS, RR, and C that need further examination, as identified in this study.

Limitations of the Study

The was limited to data collected from the Texas Hospital Data Collection Database and the analysis employed in the study. I relied on the data collection practices of the agency. The agency collects data from hospitals in Texas and willfully submit their findings and data according to the state guidelines. The hospitals distribute the surveys differently to the inpatient population but need to consider if the patient has health literacy or the level of education that allowed them to interpret the survey correctly. Finally, different statistical techniques could control biases in the data and cause the relationship between surveying and interpretation to give inconsistent values to patient satisfaction results. The data collection and analytic method measures should consider socioeconomic disparities by documenting and monitoring these areas of concern in the population. Therefore, the choice of geographic units influenced the data value.

The number of hospitals selected for the study was another limitation. The minimum number of hospitals allowable by the analytical method – G*Power analysis was selected. Finally, time constraints on the part of the researcher wouldn’t have permitted a larger sample with diverse disease conditions.

Recommendations

The results of this study may assist with collaborating existing research on the relationship between length of stay, readmission rates, and cost of patient care in other areas in Texas. The inverse relationship between average length of stay and cost of care may help caution providers who may think the relationship was always direct. Conversely, the lack of a relationship between the readmission rates and cost of care also denotes the relationship was not always direct and that many factors determined care and reimbursements. Further research using these variables with larger samples and geographical mix should be considered. Additionally, further research could be developed to analyze the results of a specific disease category and hospital segment rather than a combination. This data could help hospitals determine how to approach each patient's condition so that the data was calculated accurately within the hospitals.

The results of this study could be used as reference materials for research students and nurses to help build knowledge and support in providing care. Finally, more thorough research should be explored to analyze two or more years of data to see if significant relationships exist and under what conditions they occur. These results may serve as a guide to providers and policy makers.

Implications for Professional Practice and Positive Social Change

Professional Practice

For healthcare administrators, the research of this study provides evidence of information supporting patient care relative to length of stay, readmission rates, and cost of care. The study findings provide context for health administrators on the importance of these three variables and how their interactions impact hospital operations and profitability. The relationship between the variables was subject to other elements of care that could positively or negatively impact hospital profitability. The findings in this study indicated that a focus on other vital elements of care, such as quality of care and variability of care, to list a few, were all important variables in determining cost.

Positive Social Change

The study implications for social change by providing evidence of the benefits of results in areas of Length of Stay, Readmission rates, and Cost of care. These administrators may be able to change the approach to the quality of care that determines the construct of the work environments for clinical staff to understand the LOS and Readmission dynamics that contribute positively to patient care and profitability. The findings may also shape how health care organizations reach their patients regarding treatment, safety, positive quality of care, and the overall patient experience. Therefore, giving providers more thought and consideration would help to enhance doctor-patient communication and, ultimately, the success of the patient experience (Belasen & Belasen, 2018).

Implications for Managed Care

The analysis you provided pertains to the relationship between three key variables in the context of managed care: length of stay, readmission rate, and cost of care.

Length of Stay (LOS) and Cost of Care

The analysis indicates that there is a negative correlation between the length of stay and the cost of care. In other words, as the length of stay decreases, the cost of care tends to increase, and vice versa. This negative correlation suggests that shorter hospital stays are associated with higher costs. This could be due to several factors, such as the need for more intensive care during a shorter stay or the use of costly interventions to expedite recovery.

Readmission Rate and Cost of Care

The analysis suggests that there is no significant correlation between the readmission rate and the cost of care. In other words, changes in the rate at which patients are readmitted do not appear to have a significant impact on the overall cost of care. This finding implies that, at least within the scope of the data analyzed, readmission rates do not drive cost variations in managed care settings.

Predictive Power of LOS and Readmission Rates on Cost of Care

The analysis concludes that neither the length of stay nor the readmission rates are strong predictors of the cost of care. This means that these two variables, in isolation, do not provide a reliable basis for predicting how much the cost of care will be for a given patient or episode of care. It’s important to note that other factors, not included in this analysis, may have a more significant influence on cost variations in managed care, and these factors need to be explored further.

In summary, this analysis highlights the complex relationship between length of stay, readmission rates, and the cost of care within a managed care context. While a negative correlation between length of stay and cost suggests that shorter stays tend to be more expensive, the lack of a significant correlation between readmission rates and cost indicates that cost variations are not necessarily driven by readmission rates alone. Moreover, neither length of stay nor readmission rates alone serve as strong predictors of cost. To gain a more comprehensive understanding of cost drivers in managed care, further research and analysis may be necessary, considering additional variables and factors that influence the cost of care.

Conclusion

The overall mix in patient care must be considered in the quality of care. The CMS and other third-party payers made it a top priority for payment reimbursement, transparency, and hospital recognition. The healthcare delivery systems are tasked with providing patient safety and quality care. Although past research has been explored in LOS, RRs, and Cost care, there was limited research on providing the direct relationship between the three variables as results have been mixed occasionally. Additionally, this study showed an inverse correlation between LOS and cost of care, nor was there a statistically significant correlation between RRs and Cost of care. Furthermore, the multiple regression analysis showed no predictive relationships between the three variables. This information may assist administrators in developing systems to enhance quality care and correct their mindset about the direct relationships between these variables. The results may help care providers to develop and adopt strategies to enhance patient care for profitability.

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