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Average Length of Stay, Average Preventable Readmission Rates, and Average Total Cost of Care: Is there a Relationship?

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Abstract: **Average Length of Stay (ALOS), Average Preventable Readmission Rates (APRRs), and Average Total Cost of Care (ATCc) were examined to see if any relationship exists among the variables. Secondary data from the Texas hospital data collection database was used for the study. Out 379 acute care hospitals in Texas, 65 hospitals were selected for analysis using a G*Power analysis. Demographic analysis, Spearman's Rank correlation, and Regression Analyses were conducted to explore the relationship. The results of the Spearman's Rho correlation showed a significant negative relationship between ALOS and ATCc [ALOS – ATCc (r_s = - .271, p = .016)], and for APRRs and ATCc, there was no statistically significant relationship [APRRs – ATCc (r_s = .065, p = .564)]. The multiple regression analysis showed there was no statistically significant relationship between the variables [ALOS – ARRs – ATCc (F (2,62) = 1.584, p = .211)]. The results showed that ALOS and APRRs do not necessarily predict ATCc. Consequently, based on the study results ATCc is not solely determined by ALOS and APRRs. The absence of a significant relationship between ALOS, APRRs, and ATCc does not necessarily indicate inefficiency in practice or lack of effectiveness. The results showed that there are other mediating factors impacting care that were not assessed in the study. These factors are to be examined carefully in future studies to better understand the complex relationship between ALOS, APRRs, and ATCc. An understanding of these complex dynamics may inform managerial strategies and help with critical clinical and fiscal decisions in a healthcare setting.**

Keywords: **Average Length of Stay, Average Preventable Readmission Rates, Average Total Cost of care.**

I. INTRODUCTION

Over the last several decades, the cost of health care services in the United Stated (U.S.) rose gradually becoming a burden to patients and third-party payers. Health policy makers have focused on cost containment for several decades, to deal with the rapid rise in healthcare costs. Different measures have been introduced but virtually all of them have failed to achieve cost containment (Goyen, 2010). Despite being among the most developed nations in the world, healthcare outcomes in the U.S. lagged compared to nations with the highest healthcare cost par capital (Organization for Economic Cooperation and Development (OECD, 2023). 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 other countries. 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 over the years. For example, the Center for Medicare and Medicaid (CMS) (2020) reported that healthcare grew to about $11,582 per person and accounted for 17.7% of Gross Domestic Product (GDP); Medicare, Medicaid, private health insurance grew by 6.7%, 2.9%, and 3.7% respectively in 2019 (CMS, 2021). These statistics were among significant increases in healthcare expenditures, and the projection shows continued increases in the coming years.

Several strategies have been employed by government agencies and third-party payers to reduce length of stay (LOS), preventable readmission rates (PRR), pay-for-performance, and other cost saving measures. Yet, the U.S. global health metrics only showed signs of improvement but no significant cost reduction. Reducing the length of stay (LOS) improves financial, operational, and clinical outcomes (Hussey, Wertheimer, Mehrotra, 2013; CMS, 2021). The CMS and other third-party payers have attached quality metrics to reimbursements to encourage providers to reduce the cost of care but no interference with the quality care. However, the cost of care continues to increase and any effort to save cost tends to interfere with quality of care and patient outcomes. For example, the Center for Medicare and Medicaid (CMS) considers LOS and PRR quality measures and has tied these two metrics to reimbursement rates. Likewise, the Organization for Economic Cooperation and Development (OECD, 2023) now considers the average length of hospital stay (ALOS) as an efficiency indicator, defining it as the average number of days that patients spend in hospital. It is generally measured by dividing the total number of days stayed by all inpatients during a year by the number of admissions or discharges. The OECD has resolved that a shorter stay reduces inpatient care costs in a hospital setting, while a prolonged LOS may increase costs. Similarly, a reduced PRR saves costs, while an increased PRR results in a higher total care cost (C) for the patient and the third-party payers (OECD, 2023). 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 rate of 30-day readmissions and how long patients stay in the hospital (Length of Stay or LOS) are two things hospitals often check to see how well they are doing. The Centers for Medicare and Medicaid Services (CMS) warns the public about 30-day readmissions for all patients at a hospital. There is a CMS program called the Hospital Readmissions Reduction Program (HRRP) that is part of Medicare (CMS, 2021). This program takes away some money from hospitals if they have too many patients coming back within 30 days. The amount of money a hospital gets is also linked to how well it meets quality standards set by CMS. The Kaiser Foundation (2023) reported that the CMS under the Affordable Care Act cuts payments to hospitals that have high rates of readmissions and those with the highest numbers of infections and patient injuries. For the readmission penalties, Medicare cuts as much as 3 percent for each patient, although the average is generally much lower. Hospitals also monitor patients staying in the hospital because they get a fixed payment for treatments, no matter how many days someone stays. CMS and private payers use this payment model, so hospitals try to make the stay shorter. The cost of unplanned readmissions is 15 to 20 billion dollars annually (CMS, 2023). Preventing avoidable readmissions has the potential to profoundly improve both the quality of life for patients and the financial wellbeing of health care systems (Jencks, et al., 2009). Studies show that the reduction in LOS reduces health costs and minimizes rates of mortality and morbidity as well as hospital readmissions due to complications (Gabutti, Mascia & Cicchetti, 2017).

Hospital managers try different ways to make sure fewer patients come back within 30 days and to make the hospital stay shorter. But, making changes to help with one thing might make the other thing worse. Some studies focused on patients with a specific problem found a link between how long a patient stays and the chance of coming back to the hospital. Other studies looked at certain illnesses, like heart failure, and found that either a shorter or longer stay could make the chance of coming back higher. So, hospitals must be careful with the strategies they use because it can affect both readmission rates and how long patients stay in the hospital.

This study examined average length of stay (ALOS), average preventable readmission rates (APRRs), and the average total cost of care (ATCc). 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). The National Academy of Medicine (NAM), previously the Institute of Medicine (IOM) outlined six goals for improving healthcare including, timeliness, safety, effectiveness, efficiency, equitability, and patient-centeredness. Despite these recommendations, the healthcare industry continuously faces challenges in meeting these overarching quality goals, resulting in a more financial burden for providers, patients, and third-party payers. To meet these quality goals and 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 (Vento, Cainelli, & Vallone, 2018). The practice of defensive medicine may include the ordering of excessive medical tests and procedures, prolonged LOS, and increased 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.

Problem Statement

The prolonged financial burden on third-party payers, patients, and providers due to increased readmissions and extended lengths of stay has been a persistent issue. Despite efforts to establish consistent reimbursement metrics, studies reveal mixed results (Upadhyay, Stephenson, & Smith, 2019), prompting the need for further investigation into the association between length of stay, readmission rates, and cost of care. Investigations of this nature are needed to build a knowledge base for informed clinical decision-making in the face of these complex healthcare challenges.

Purpose of the Study

The purpose of this descriptive correlational study is to investigate the relationship between ALOS, APRRs, and C of care, in order to provide a basis for making reliable fiscal and clinical decisions. Researchers have investigated the relationship between LOS and RRs with conflicting results. As cost remains one of the single main concerns for all healthcare stakeholders, the need to examine these triadic elements is further supported. In addition, further research has validated the complex interactions that occur among these three elements. For example, Upadhyay et al. (2019) recommended further studies be done to examine the relationship between LOS, RR, and C, to help provide more insight into the literature.

Research Questions

The following research questions guided the study:

RQ 1: What is the relationship between Average Length of Stay (ALOS) and Average Total Cost of care (ATCc)?

H_{1o}: There is no statistical significance between ALOS and ATCc.

H_{1a}: There is statistical significance between ALOS and ATCC.

RQ 2: What is the relationship between Average Preventable Readmission Rates (APRRs) and Average Total Cost of care (ATCc)?

H_{2o}: There is no statistical significance between APRRs and ATCc.

H_{2a}: There is statistical significance between APRRs and ATCC.

RQ 3: Do ALOS and APRR significantly predict the ATCc in Texas hospitals?

H_{3o}: ALOS and APRR do not significantly predict Acc in Texas hospitals.

H_{3a}: ALOS and APRR do significantly predict ATCc in Texas hospitals.

II. CONCEPTUAL FRAMEWORK AND LITERATURE REVIEW

A. Conceptual Framework

The Donabedian model, proposed by Avedis Donabedian (1988), is a widely used framework for assessing and improving the quality of healthcare and provides the conceptual framework for this study. The model consists of three key components: structure, process, and outcomes. These components are interrelated and provide a comprehensive approach to understanding and enhancing the quality of patient care in healthcare organizations. Since ALOS and APRRs are associated with the quality of care provided in hospitals, the Donabedian model is the best fit to assess these variables.

Structure refers to the organizational and environmental factors that shape the context within which care is provided (Donabedian, 2003). This includes the physical facilities, human resources, equipment, policies, and other elements that influence the delivery of healthcare services. The quality of the healthcare infrastructure, availability of skilled staff, and access to necessary resources all impact patient care. Adequate staffing levels, well-maintained facilities, and appropriate technology contribute to a positive patient experience and effective care delivery. The structure component may influence ALOS by affecting the efficiency of care delivery, availability of beds, and the overall capacity of the healthcare organization.

Process refers to the activities and interactions that occur during the delivery of healthcare services (Donabedian, 2003). It includes the methods, techniques, and sequences of actions employed to achieve specific outcomes in patient care. Effective clinical processes, communication, and coordination among healthcare professionals are essential for ensuring the delivery of high-quality care. Efficient and well-coordinated processes contribute to a reduction in preventable readmissions and enhance the overall patient experience. The quality-of-care processes, including post-discharge planning and follow-up, can impact preventable readmissions. Efficient and well-coordinated processes may contribute to cost-effective care, potentially reducing the overall cost of care.

Outcomes represent the results of healthcare activities and interventions, including changes to health status, patient satisfaction, and other indicators of the impact of care (Donabedian, 2003). Outcomes are the ultimate measure of the effectiveness and quality of patient care. Positive outcomes indicate that the healthcare organization has succeeded in delivering care that meets patient needs. Effective care processes and a well-structured healthcare environment can contribute to positive outcomes, potentially leading to shorter lengths of stay. Positive outcomes, such as successful post-discharge care and patient education, can contribute to lower preventable readmission rates. Efficient processes and positive outcomes may contribute to cost containment, impacting the overall total cost of care.

Numerous studies employing the Donabedian model have contributed valuable insights to diverse healthcare contexts. For example, Moore et al. (2015) utilized the model to assess the quality of care in a Canadian trauma hospital, establishing statistically significant correlations between structural elements, procedural aspects, and ultimate outcomes such as hospital length of stay and readmissions. Binder, Torres, and Elwell (2021) conducted a facility-level case study during the early stages of the COVID-19 pandemic, employing the Donabedian model to guide changes in structure and processes for emergency care. Their findings emphasized that adaptive alterations, aligned with the model, were crucial for maintaining high-quality clinical outcomes and ensuring the safety and engagement of emergency department staff. McCullough et al. (2023) reviewed existing research articles using the Donabedian model, revealing a predominant medical model approach with limited consideration of primary health care (PHC) principles and nurse experience. This raises questions about the model's effectiveness in evaluating PHC services aligned with national and international population health goals. Tossaint-Schoenmakers et al. (2021) explored the integration of eHealth in regular healthcare using the Donabedian model, identifying three crucial principles: incorporating the care receiver's role into organizational structure and daily processes, aligning technology with the organizational structure, and deploying human resources in line with desired outcomes. The Donabedian model emerges as a vital tool for comprehensively measuring healthcare quality across diverse applications.

In summary, the Donabedian model provides a comprehensive framework for understanding the quality of patient care in healthcare organizations. The interplay between structure, process, and outcomes is crucial in addressing key indicators such as average length of stay, average preventable readmission rate, and total cost of care. By focusing on each component of the model, healthcare organizations can systematically evaluate and improve the quality of care they provide to patients.

Review of Related Literature

Various studies have been conducted investigating the three variables and their interactions in varying situations.

Average Length of Stay (ALOS). Hospital inpatient length of stay has severe financial implications for stakeholders and the entire healthcare industry (Rachoin et al., 2020). The Health Catalyst (n.d.) reported that systematic data-driven approaches reduce length of stay and improves care delivery. Improving and reducing length of stay (LOS) improves financial, operational, and clinical outcomes by decreasing the costs of care for a patient. It can also improve outcomes by minimizing the risk of hospital-acquired conditions. Citing one prominent hospital as an example, the author's noted that Memorial's commitment to a data-driven, multi-pronged approach to reducing LOS has produced the desired results in one year, including $2 million in cost savings. This result was achieved by decreasing LOS and utilization of supplies and medications, and improved care coordination and physician engagement.

The Affordable Care Act (ACA) mandated accountability and transparency in hospital operations requiring hospitals to reveal the financial stress they undergo due to prolonged LOS. Mandatory reporting and transparency requirements about the quality-of-care data has been a growing issue for hospitals and health services organizations. Many studies have investigated the impact of LOS on hospital revenues and patients alike. For example, Wu et al. (2022) conduct a cross-sectional study to examine the associations between the introduction and discontinuation of use of diagnosis-related groups and length of stay, volume of care, in-hospital mortality, and emergency readmission rates among patients in public acute care hospitals in Hong Kong. The results showed that the introduction of DRGs was associated with shorter hospital stays and increased hospital volume, and discontinuation was associated with longer stays and decreased volume. This means that the discontinuation of DRGs was associated with longer hospital stays and fewer hospital admissions but with no change in quality indicators. Longer hospital stays are often associated with a high cost of care. Upadhyay, Stephenson, and Smith (2019) conducted a longitudinal study to examine whether readmission rates, made transparent through Hospital Compare, affect hospital financial performance by examining 98 hospitals in the State of Washington from 2012 to 2014. Readmission rates for acute myocardial infarction (AMI), pneumonia (PN), and heart failure (HF) were examined against operating revenues per patient, operating expenses per patient, and operating margin. The analysis indicated that a reduction in AMI readmission rates is related to increased operating revenues as expenses associated with costly treatments and unnecessary readmissions are avoided. Additionally, reducing readmission rates is related with an increase in operating expenses. As a net effect, increased PN readmission rates may show marginal increase in operating margin because of the higher operating revenues due to readmissions. However, as readmissions continue to happen, a gradual increase in expenses due to greater use of resources may lead to decreased profitability for the hospital. While improved patient management may decrease cost in a multitude of ways, four broad, interrelated categories of cost savings are identified: decreased LOS, reduced number of readmissions, improved resource allocation, and improved long-term health (Haque, Demidowich, Sidhaye, Golden, & Zilbermint, 2021).

Average Preventable Readmission Rate (APRR). The CMS (2023) refers to average preventable readmission rate as the percentage of patients who are readmitted to a hospital within a specific time frame due to conditions that could potentially be prevented or managed more effectively. This metric is often used in healthcare quality assessments to evaluate the effectiveness of care delivery and identify areas for improvement in preventing avoidable hospital readmissions. According to the Agency for Health Research and Quality (AHRQ) (2023), hospital readmissions are categorized by procedure, diagnosis, and by payer. The agency noted that by procedure, one in five patients with common conditions of amputation, heart value, and debridement of wounds and infection; and one in three for kidney related diseases are readmitted. By diagnosis, one in for patients with common conditions of congestive heart failure, schizophrenia, and renal failure; and one in three of less frequent diagnosis of gangrene and sickle cell are readmitted. As for readmissions by payer systems, the AHRQ noted that Medicare and Medicaid have the highest readmissions for both procedural and diagnosis compared to private payers. Kwok, et al (2021) noted that hospital readmissions for heart failure conditions is a major financial problem to healthcare systems. The CMS introduced the Hospital Readmission Reduction Program (HRRP) with the aim to reduce excess readmissions among Medicare beneficiaries by applying financial penalties to hospitals with higher-than-expected 30-day all-cause readmission rates among hospitalizations for any of the conditions or procedures considered in the program.

In another study, Chopra, Wilkins, and Sambamoorthi (2016) investigated the association between index hospitalization characteristics and the risk of all-cause 30-day readmission among high-risk Medicaid beneficiaries using multi-level analyses. The result of the study was that Adults with greater lengths of stay during the index hospitalization were more likely to have 30-day readmissions. The length of stay depended on the nature of hospitalization characteristics of the patients including, the type of diagnosis or diseases, chronic conditions, the type of population. The authors also noted that the readmission patterns of the Medicaid population differ from those of the geriatric Medicare population, from both clinical and socio-economic perspective. Haque, Demidowich, Sidhaye, Golden, and Zilbermint (2021) noted that patients who experience hyperglycemia during their hospitalization are discharged with one of the six diagnoses under the Centers for Medicare and Medicaid HRRP. Such patients may have a higher 30-day readmission rate (Gaines, 2018). Similarly, hypoglycemia adversely impacts drivers of hospital cost. In a study of nearly 44,000 hospitalizations in 2015–2016, it was found that patients experiencing normoglycemia had an average length of stay (ALOS) of 7.8 days and $11,039 average total cost of stay compared to those experiencing severe hypoglycemia, who had an average ALOS of 14.4 days and $21,444 average total cost per stay (Business Wire, 2019).

Rachoin et al. (2020) sought to analyze the impact of length of stay on readmission risk in an inpatient general medical population to assess whether patients with a lower length of stays were readmitted more frequently to the hospital. The results showed that out of 91,723 patients included in the study of which 10,598 (11.6%) were readmitted. The geometric LOS for all patients was 5.37 days and was higher in readmitted patients. The multivariate regression analysis revealed that a high LOS was associated with a higher likelihood of readmission. The authors found that general medical patients with a higher LOS had a higher likelihood of being readmitted to the hospital after adjusting for other variables. Hospitals may prefer to reduce readmissions rates based on the certain diagnostic related groups (DRGs). In fact, Benito et al. (2022) specifically suggested that early discharge of patients with knee surgery may serve to independently decrease readmission rates regardless of the choice of perioperative protocol. Benito *et al's* position was supported by Glorimar (2022) who noted that patients with mental illness at risk of being prematurely discharged may suggests insights into quality initiatives aimed at reducing rapid readmissions into psychiatric inpatient care. Proper discharge planning and quality care often help reduce readmission.

Wong, Poon, Cheung *et al.* (2022) examined the relationship between patient experience and hospital readmission at a system level by linking anonymous experience survey data with de-identified longitudinal hospital administrative admissions data. The study demonstrated the feasibility of routine record linkage, with the limited intrusion of patients' confidentiality, for evaluating health care quality. It also highlights the significant association between readmission through planned readmission and a higher score for overall quality of care received. Similarly, Yacoub et al. (2021) found out that LOS can be reduced by implementing a quality improvement intervention, driven by a multidisciplinary committee involving healthcare personnel, to facilitate the optimal discharge mechanism through available hospital resources and services.

Preventable readmissions are those that healthcare providers believe could have been avoided through better care during the initial hospitalization and post-discharge period. This metric is often used in healthcare quality assessments to evaluate how effectively a hospital is managing patient care to minimize unnecessary return visits. The goal is to reduce preventable readmissions, which can lead to better patient outcomes, improved quality of care, and cost savings. Haque et al. (2020) recommended providers take all necessary measures to care for patients in critical conditions including monitoring and surveillance measures couple with quality treatment in order to avoid or limit readmissions. In essence, the average preventable readmission rate provides insight into the hospital's ability to provide comprehensive and effective care, not only during the initial hospital stay but also in the transitional period following discharge. Lowering preventable readmission rates is a key focus for healthcare providers and policymakers as part of efforts to enhance the overall quality and efficiency of healthcare delivery. In this study, there was no statistically significant relationship between APRR and ATCc.

The Average Total Cost of Care encompasses all costs associated with a patient's care, including hospitalization, procedures, medications, and post-acute care. ALOS and APRRs can impact the total cost of care. Shorter ALOS and lower readmission rates can lead to cost savings. Hospitals and healthcare systems often strive to deliver high-quality care while controlling costs to provide value-based healthcare. The relationship between these factors is interconnected and influenced by various factors, including the hospital's efficiency, quality of care, patient population, and healthcare policies. Reducing ALOS and readmission rates without compromising quality can lead to cost savings and improved patient outcomes. Healthcare providers and policymakers are increasingly focused on achieving a balance between these factors to ensure cost-effective, high-quality care. Initiatives like value-based care and care coordination aim to optimize these metrics by providing comprehensive and efficient care while minimizing readmissions and controlling costs. The specific relationships can vary between hospitals and healthcare systems, and they are subject to ongoing research and quality improvement efforts in the healthcare industry.

There have been mixed results from several studies involving preventable readmissions, length of stays, and cost of care 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. This dissimilarity results presents a gap. The authors recommended 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 expenditure 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 of 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.

III. METHODOLOGY

Procedure

I employed a quantitative descriptive correlational approach to investigate the interrelation between average length of stay, preventable readmission rates, and the cost of care. Secondary data for 2018 from the Texas Healthcare Information Collection Center for Texas hospitals accessible at https://dshs.texas.gov/thcic was used. Acute care hospitals, specializing in immediate evaluation and treatment for severe medical conditions, were included in the report. The Texas Inpatient Hospital Data File was accessed and is publicly available and easily obtainable. Hospitals with complete data and licensed (inclusion criteria) were randomly selected for analysis, while those with incomplete data without license (exclusion criteria) were discarded. Complete data include specified accreditation and sufficient data on inpatient length of stay, readmission rates, and cost of care for acute myocardial infarction (AMI), pneumonia (PN), and heart failure (HF). The data on these variables were crucial for addressing research questions, offering data points for both dependent and independent variables.

From a total of 517 hospitals of which 379 are acute, serving nearly 29,000,000 people in Texas, 120 were targeted, focusing on 65 randomly selected accredited hospitals.

Sampling and Sampling Procedures

Sample and Effect Size

G*Power and sample size analyses were conducted using SPSS 28 software to achieve the recommended level of confidence (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 Spearman's Rank Correlation analysis. Using a multiple regression model on G*Power software with two predictors indicates that a sample size of 65 participants was needed.

Instrumentation and Operationalization of Constructs

Instrumentation. I used secondary data in the study, which does not require research instruments (Creswell, 2018). I specifically looked for information on hospital demographics, ALOS, APRR, and ATCc for conditions under the same Diagnostic Related Groups (DRGs). *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. *Variables* - The three variables under investigation were *Total Cost of Care* – was the dependent variable (DV); *Average Length of Stay* – was the independent variable (IV), and *Average Preventable Readmission Rates* – was also the independent variable. The average preventable readmission rates represent 30-day readmission rates [ratio data] evaluates what happens to patients once they leave the hospital after receiving care for certain conditions.

IV. RESULTS

Data Analysis

The statistical software SPSS 28 was used for analysis. The following analyses were done including descriptive statistics, Spearman's Rank Correlation, and multiple regression.

i. Demographic 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 1 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.

Table 1: Ownership of Hospitals

	Ownership			
	Frequency	*%*	*Valid %*	*Cum %*
FP	34	52.3	52.3	52.3
NP	22	33.8	33.8	86.2
P	9	13.8	13.8	100.0
Total	65	100.0	100.0	

Note: FP = For Profit; NP = Nonprofit; P = Public

The hospitals were categorized into metro and non-metro hospitals and were all licensed. 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, all the hospitals included in the dataset were acute license-type hospitals (Table 2).

Table 2: Hospital Metro Status and Licensed Type

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

Furthermore, I evaluated the procedural 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 3).

Table 3: Procedural Groups

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

I also evaluated the individual patient status regarding transfer 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 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 4).

Table 4: Patient Status

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

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

ii) Hypotheses Testing

Before conducting any hypothesis testing, an exploratory data analysis was performed, assessing the normality distribution of variables through the Kolmogorov-Smirnov (K-S) test. The obtained p-value (< 0 .05) indicated non-normal distribution of the variables. Consequently, a Spearman Rank Correlation was employed to explore potential relationships between the variables.

RQ 1*: *What is the relationship between ALOS and ATCc? To test the relationship between ALOS and ATCc, a Spearman rank correlation was utilized. The statistical analysis revealed that the mean average length of stay was 4.81 days (SD = 2.87 days), and the mean average total charges were $60,347 (SD = $70,637). Notably, a significant negative relationship emerged between average length of stay and average total charges or Cost of care [ALOS – ATCc (r_s = - .271, p = .016] at the .05 alpha level, as detailed in Table 5.

Table 5: Correlation between ALOS and ATCc

Correlation			
Spearman's Rho		1	2
	ALOS	1.000	- .271*
	ATC	- .271*	1.000

Correlation significant at the 0.05 level (2-tailed); ALOS = average Length of Stay; ATCc = Average Total Cost of care

RQ 2: What is the relationship between APRR and ATCc? Again, to test the relationship between the APRR and ATCc, a Spearman Rank Correlation was conducted for APRR and ATCc. Again, the Spearman correlation analysis evaluated the relationship. The descriptive statistics showed that the mean total charges were $60,347 (*SD* = $70,637). On the other hand, the average readmission rate was 29.95 days (*SD* = 53.119 days). The analysis findings show no statistically significant relationship between the average total charges (cost) and the average preventable readmission rate, Spearman's rho, r = .065, p = .564 (See Table 6, correlations).

Table 6: Correlations between APRR and ATCc

Correlation			
Spearman's Rho		1	2
	APRR	1.000	.065
	ATC	.065	1.000

Correlation significant at the 0.05 level (2-tailed); APRR = Average preventable Readmission Rates; ATCc = Average Total Cost of care

Multiple Regression Analysis for ALOS, APRR, and ATCc

A multiple regression analysis was conducted to examine the relationship between ALOS, APRR, and ATCc. The regression model summary indicated an adjusted R-Square of .018, representing the effect size. This implies that the two predictors could only account for 1.8% of the variation in the dependent variable. The ANOVA model results revealed that the regression model was not statistically significant, [F (2,62) = 1.584, p = .211]. The study found that ALOS and APRR were unable to predict the Cost of Care.

Table 7. Regression Analysis

Model Summary

R	*R^2*	*Adjusted R^2*	*Std. EE*	*DW*
.221[a]	.049	.018	69994	1.993

ANOVA

Model	*SS*	*df*	*MS*	*F*	*Sig*
Regression	155	2	779	1.591	.211[b]
Residual	3.03E+1	62	489		
Total	3.193E+1	64			

Coefficient[a]

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

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

V. DISCUSSION

Average Length of Stay

The relationship between the average length of stay, average preventable readmission rates, and average total cost of care in healthcare systems in general can be complex and multifaceted. Hospitals aim to reduce ALOS while maintaining quality care. A longer ALOS increases costs, as it requires more resources and hospital bed utilization as indicated by Rachoin et al. (2020). However, in this study, the ALOS was negatively correlated to the ATCc. A negative correlation between ALOS and ATCc in a healthcare setting typically means that as the ALOS decreases, the ATCc tends to increase, and vice versa. This finding was contrary to that of Rachoin et al. (2020). Several factors can contribute to this negative correlation including the lengthier the hospital stay, the higher the cost of care. However, there are specific situations where an extended stay may be correlated with potentially lower overall costs for the patient. Several examples illustrate these circumstances:

Firstly, in instances where complications are paramount, an extended hospital stay may be necessary for continuous monitoring and management. This proactive approach allows for early detection and intervention, averting the development of severe health issues that could require expensive treatments in the future. Secondly, postoperative care, especially following complex or major surgeries, may necessitate a more prolonged hospital stay for close monitoring, effective pain management, and rehabilitation. This extended care period contributes to improved recovery outcomes, potentially reducing the likelihood of complications that might lead to additional costs.

In cases requiring rehabilitation services, a longer hospital stay can facilitate a more comprehensive and effective rehabilitation program, leading to better functional outcomes and a reduced need for additional rehabilitation services or readmission after discharge. For patients with chronic conditions, an extended hospital stay may be beneficial for intensive education, counseling, and management strategies. This approach can result in better self-management, adherence to treatment plans, and reduced reliance on emergency services over time.

Additionally, in situations where a patient's condition is unstable or requires significant stabilization, a longer hospital stay may be necessary to ensure the patient is in a controlled and manageable state before transitioning to outpatient care. This finding is consistent with the recommendation of Haque et al. (2020) who recommended providers take all necessary measures to care for patients in critical conditions including monitoring and surveillance measures couple with quality treatment. This preventive measure can help avoid readmissions and emergency visits. It's crucial to note that these examples are context-dependent, and the relationship between length of stay and overall cost can vary based on the specific medical condition, treatment protocols, and the healthcare system. Advances in healthcare delivery and a focus on value-based care aim to optimize patient outcomes while minimizing unnecessary costs, including prolonged hospital stays.

Average Preventable Readmission Rates

The study's findings highlighted a lack of significant correlation between APRR and ATCc in a healthcare setting. This absence of a strong correlation may be influenced by various factors. Firstly, the provision of high-quality care in hospitals may result in lower readmission rates, as patients are less likely to experience complications. However, the cost of delivering high-quality care, involving investments in technology, staffing, and specialized services, may contribute to an increased ATCc. This disparity in cost and quality could diminish the correlation between readmission rates and costs. Secondly, the effectiveness of post-discharge care and follow-up plays a crucial role in reducing readmissions. Healthcare facilities investing in comprehensive post-discharge care, including home health services, outpatient follow-up appointments, and patient education, may achieve lower readmission rates. Nevertheless, this approach can elevate the overall cost of care, further diminishing the correlation between readmission rates and costs. Thirdly, the patient mix served by a healthcare facility varies significantly. Hospitals treating a more medically complex or older population may experience higher readmission rates, irrespective of the quality of care provided. This demographic variation could contribute to a weak correlation between readmission rates and costs.

Additionally, healthcare reimbursement models and policies can impact the relationship between readmission rates and costs. Variations in reimbursement structures, such as value-based care models incentivizing reduced readmissions, can affect the correlation, especially when different hospitals operate under diverse reimbursement frameworks. Moreover, geographic and socioeconomic factors, including patients' access to healthcare services, socio-economic status, and the prevalence of chronic diseases, can influence readmission rates. These factors, along with variations in the cost of living and healthcare infrastructure, may not exhibit a strong correlation with each other, further complicating the relationship between readmission rates and costs. Hospital-specific practices and protocols also contribute to the lack of a strong correlation. Hospitals with more effective care transition processes, better discharge planning, or robust post-discharge follow-up programs may reduce readmissions without significantly affecting costs.

Finally, variations in data collection and reporting practices among healthcare facilities can contribute to the absence of a strong correlation. Inaccurate or inconsistent data reporting may obscure any potential relationship between readmission rates and costs.

In conclusion, the absence of a significant correlation between readmission rates and costs does not necessarily indicate a lack of influence between the two. The complex and interacting nature of multiple factors, coupled with diverse strategies employed by healthcare facilities, contributes to the nuanced relationship between these metrics.

ALOS and APRRs as predictor variables for ATCc

In this study, the ALOS and APRR were found to be ineffective predictors of ATCc. Several potential reasons could explain the limited predictive capability of a multiple regression model incorporating both ALOS and APRR as predictor variables. Firstly, the presence of multicollinearity between ALOS and APRR may be a contributing factor. High correlation between these predictor variables can result in multicollinearity, where they provide similar information in the model, making it challenging to discern their individual effects on Average Cost of Care and weakening the model's predictive power. Secondly, an insufficient sample size may compromise the model's effectiveness in multiple regression analysis. Inadequate cases or an unrepresentative dataset can lead to an unreliable regression model, affecting its ability to predict Average Cost of Care accurately. Thirdly, the assumption of linear relationships in the model may not hold true if the actual relationships between ALOS, APRR, and ATCc are nonlinear. Nonlinear relationships can hinder the model's predictive accuracy (Creswell, 2018), and the data in the study did not exhibit a linear relationship.

Other potential factors influencing the model's performance include unaccounted-for variables that significantly impact Average Cost of Care, such as hospital size, patient demographics, or specialized services. Omitted variables in the analysis can undermine the model's ability to capture the full spectrum of influential factors. Measurement errors in data collection and reporting, including inaccuracies in ALOS, APRR, or ATCc, can compromise the model's predictive power. The choice of model specification, including the functional form and inclusion/exclusion of interaction terms, may affect the model's predictive capabilities. A poorly specified model may not effectively capture the intricate relationships between variables. Temporal factors, such as changes in healthcare costs over time due to inflation, evolving medical technology, or shifts in healthcare policies, may not be adequately addressed by a regression model, limiting its predictive ability. The dataset's heterogeneity, encompassing diverse healthcare facilities with varying practices, patient populations, and case mixes, poses a challenge to creating a universally applicable predictive model. Finally, the inherent complexity of healthcare systems, influenced by numerous interrelated factors, may surpass the capacity of a multiple regression model. Consideration of more variables, exploration of non-linear relationships, addressing multicollinearity, and utilizing a larger and more representative dataset, along with expert domain knowledge, may enhance the model's predictive power. Tailoring models to specific healthcare contexts may be crucial in capturing the unique factors influencing costs.

Limitation of the Study

The study is limited to 65 hospital data of the 2018 Texas Hospital Data collection database. In addition, a descriptive correlation approach was used in the investigation. I did not consider other mediating factors that impact care such as hospital specific practices, socioeconomic status, post discharge and follow-up policies; to list a few.

Implications for Research

Based on the study's results, several implications for further research merit considerations. To begin, researchers are encouraged to delve into the specific factors influencing the negative correlation between average length of stay and average total cost of care. Exploring interventions or practices that contribute to shorter stays without compromising patient outcomes could offer valuable insights, informing the development of cost-effective healthcare strategies. Furthermore, despite the lack of significant differences between average preventable readmission and average total cost of care, further investigation could focus on specific subgroups or conditions where preventable readmissions might exert a more pronounced impact on costs. This nuanced analysis may involve exploring patient populations or types of interventions that warrant closer examination. The study's finding that average length of stay and average readmission ratio rate do not predict average total cost of care raises questions about additional predictors. Further research could explore other variables or factors that may significantly contribute to the variation in total costs, providing a more comprehensive understanding of cost drivers in healthcare.

Conducting longitudinal studies is suggested to track changes over time and unveil dynamic patterns in the relationships between length of stay, preventable readmissions, and total costs. This longitudinal approach may capture shifts in healthcare practices, policies, or patient demographics that influence these associations. Incorporating qualitative research methods, such as interviews or focus groups with healthcare professionals, patients, and administrators, is recommended for a deeper understanding of the underlying reasons behind observed correlations. Qualitative investigations can provide a richer context, offering valuable insights that enhance the interpretation of quantitative findings. By addressing these research implications, future studies can contribute to a more nuanced and comprehensive understanding of the complex relationships in healthcare. By addressing these implications in further research, researchers can contribute to a more comprehensive understanding of the complex relationships between length of stay, preventable readmissions, and total costs in healthcare.

Implications for Practice

Based on the study's findings, several practical implications emerge for healthcare professionals and organizations. Firstly, practitioners may benefit from strategies aimed at optimizing the length of stay without compromising patient outcomes. This could involve streamlining processes, implementing evidence-based practices, and emphasizing efficient care delivery to manage costs effectively. Secondly, despite the study not revealing a significant difference between average preventable readmission rates and average total cost of care, practitioners should remain vigilant in addressing preventable readmissions. Implementing interventions, such as improved discharge planning and post-discharge support, can contribute to overall cost-effectiveness and better patient outcomes. Thirdly, the study suggests adopting a holistic approach to care planning. Practitioners should consider factors beyond length of stay and readmission rates, including the appropriateness of interventions, patient education, and coordination of care, to effectively manage costs.

Additionally, healthcare organizations are encouraged to embrace a culture of continuous quality improvement. Regular assessment of practices, policies, and outcomes will enable organizations to adapt to evolving healthcare landscapes, including ongoing evaluations of interventions aimed at reducing length of stay and preventable readmissions. Tailoring interventions to specific patient populations or conditions is also emphasized. Recognizing that different patient groups may exhibit varying relationships between length of stay, preventable readmissions, and total costs, practitioners should personalize interventions to enhance care delivery and resource allocation. Furthermore, investing in transitional care programs is highlighted as beneficial. Ensuring smooth transitions from hospital to home, providing adequate support post-discharge, and promoting patient education can contribute to preventing unnecessary readmissions and improving long-term outcomes. The study underscores the importance of data-informed decision-making in clinical and administrative settings. Practitioners should regularly analyze healthcare data, including length of stay, readmission rates, and costs, to gain insights into the effectiveness of current practices and identify areas for improvement. Lastly, enhanced collaboration and communication among healthcare providers, departments, and care settings are crucial. Improving communication between inpatient and outpatient care teams, as well as fostering collaboration across disciplines, can contribute to smoother transitions of care and positively impact both length of stay and preventable readmission rates. Incorporating these implications into practice can help healthcare professionals and organizations enhance the efficiency, effectiveness, and cost-effectiveness of care delivery while maintaining a focus on patient outcomes.

Implications for Methodology

The study has implications for refining methodology in future research. Firstly, researchers should explore causation and experimental design. While descriptive correlational studies offer valuable insights into associations, introducing experimental or quasi-experimental designs can illuminate causal relationships between variables, fostering a more robust comprehension of the factors impacting length of stay, preventable readmissions, and total costs. Secondly, the adoption of longitudinal study designs may prove beneficial. Such designs can effectively capture changes over time, revealing trends and patterns that contribute to a more comprehensive understanding of how variables evolve and interact, particularly in the context of healthcare outcomes and resource utilization over extended periods. Additionally, supplementing quantitative findings with qualitative methods can provide a richer context, uncovering the perspectives of healthcare professionals, patients, and administrators. Qualitative research enhances the interpretability of quantitative results, offering a deeper understanding of the factors influencing length of stay, preventable readmissions, and total costs. Lastly, extending the analysis through advanced statistical techniques, like multivariate analysis, can unveil simultaneous relationships between multiple variables, identifying nuanced associations and potentially confounding factors. Adopting a mixed-methods research design, which integrates both quantitative and qualitative approaches, can further contribute to a holistic understanding of the intricate relationships in healthcare, allowing for the triangulation of findings. By incorporating these methodological considerations, future research endeavors can elevate the depth, validity, and applicability of findings, contributing to a nuanced understanding of the factors influencing healthcare outcomes and costs.

VI. CONCLUSION

It is important to note that the relationship between ALOS and Average Cost of Care is complex. Reducing ALOS while maintaining or improving the quality of care is a goal in many healthcare systems as it can result in cost savings and better patient experiences. However, achieving this balance often requires careful planning, process improvements, and a focus on value-based care. Even though increased average length of stay and preventable readmission rate increases cost of care, providers should know that this is not always the case if quality practices are upheld with careful planning.

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