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The Relationship Between Length of Stay, Hospital Characteristics, and Cost of Care in Acute Care Hospitals in the U.S.

Maria Mikhataykina
Walden University

Walden University

College of Management and Technology

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Maria Mikhataykina

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Review Committee
Dr. Irene Williams, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Charlie Shao, Committee Member, Doctor of Business Administration Faculty

Dr. Alexandre Lazo, University Reviewer, Doctor of Business Administration Faculty

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

Walden University
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Abstract

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Maria Mikhataykina

MBA, Texas Woman's University, 2013

BSN, University of Texas, 2012

Doctoral Study Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Business Administration

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Abstract

Rising healthcare costs make access to healthcare less accessible for many individuals. Hospital administrators, payer stakeholders, and patients are concerned with rising healthcare costs, as many patients may be hindered from receiving quality health care. Grounded in complex adaptive systems theory, the purpose of this quantitative correlation study was to examine the relationship between inpatient hospital (a) LOS, (b) bed size, (c) location, (d) region, (e) control/ownership, and cost of care. The participants were community hospitals participating in the Nationwide Inpatient Sample (NIS) data collection tool of the Healthcare Cost and Utilization Project. The results of the multiple linear regression were significant, $F(4, 299) = 10.60$, $p < .001$, $R^2 = .15$. In the final model, only two of the predictors were significant, with the length of stay providing a higher contribution ($t = 6.22$, $p = .00$, $\beta = .34$) than control/ownership of hospital ($t = 2.78$, $p = .01$, $\beta = .15$). A key recommendation is for healthcare leaders to drive efficiency of hospital operations decreasing length of stay and market control/ownership structure of the hospital to the public educating patients to make better choices as they chose providers for their healthcare needs. The implications for positive social change include the potential to increase access to healthcare and support public education.

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Dedication

This work is dedicated to my family, friends, and colleagues. To my amazing and supportive husband, to my children who sacrificed their time with their mother, to my friends who lifted me up in the moment of doubt, and to my amazing colleagues who had my back every step of the way. I want to say, *THANK YOU* because it would not be possible without you.

Acknowledgments

I am most grateful to my committee chair, Dr. Williams, and Dr. Shao for taking great responsibility supporting me through the journey. Thank you for believing in me even when I did not believe in myself. Thank you for being there every step of the way. Thank you for your encouragement, patience, support, and invaluable wisdom that guided me through this journey.

My deepest gratitude goes out to my colleagues at UT Physicians and HCA Healthcare, where I developed the passion for better understanding the problem of healthcare cost complexity.

Table of Contents

List of Tables

List of Figures

Section 1: Foundation of the Study

Having access to high quality healthcare is a right not a privilege. In the 2020 National Health Interview survey, 6.7% of adults failed to obtain medical care due to cost. Nearly 90% of people have a usual place to go for medical care without thinking about the impact of their choice, and the cost they occur (CDC, FastStats). There is a need to better understand what drives the healthcare cost and how we can better control it.

Historical Background

Healthcare in the United States is a complex and expensive system. Sturmberg and Bircher (2019) shared new drugs and technical innovations make healthcare more costly, while the system's complexity should promote cost reduction and quality of care. Sadly, rising healthcare costs do not mean high quality of care, making healthcare less accessible and affordable (Crowley et al., 2020). Glover et al. (2020) recommended looking at healthcare through the Complex Adaptive System (CAS) theoretical lenses to understand the system's impact on the cost. Sturmberg and Bircher (2019) thought that CAS helps lower the price, while Penney et al. (2018) recommended looking at healthcare agents' complexity and relationships. However, it is unclear what impact each agent within complex healthcare has on the cost reduction strategies. As a researcher of this study, I will examine the relationship between the length of stay, hospital characteristics, and healthcare cost while reviewing the secondary data set obtained from the Healthcare Cost and Utilization Project (HCUP).

Organizational Context

Healthcare is an essential service with a demand on the rise. U.S. acute care facilities face significant financial pressure making understanding of healthcare costs critical (Sarvepalli et al., 2019). The healthcare industry has made no progress towards healthcare cost reduction (Cai et al., 2020). Hospital operation is a complex environment that affects hospital profitability. Due to increased healthcare costs, healthcare accessibility continues to be a hot topic for discussion and research. Lack of understanding of how structural, financial, and operational elements relate to each other creating a gap for future research. Programs like HCUP provide insight into data analytics within healthcare, creating opportunities to understand better and review the impact of complex healthcare interactions. In reviewing this doctoral work, I will better understand relations between variables while providing insight from a clinical standpoint.

As a board-certified registered nurse and doctoral business student, I represent clinical and business knowledge within my field of study. I notice the mission of delivering the best care or making healthcare more equitable in many acute care facilities regardless of size, geographical location, or organizational structure. Using national secondary data like HCUP will allow me to review the big picture while not getting lost in the weeds of each organization. Hospital characteristics, length of stay, and cost may vary drastically among the organizations, creating further need for research (Martin, 2018). HCUP data does not discriminate based on geographical location, market needs, payer contracts, hospital affiliations, and legal boundaries (NIS, 2018). HCUP data is a great way to look at relations between the variables without bias.

Problem and Purpose

In 2018, U.S. healthcare spending reached 3.6 trillion dollars, equivalent to 17.7% of GDP (Cai et al., 2020). An extended hospital stay is a leading part of medical costs for healthcare organizations, insurance companies, and patients leading to medical complications and other costly, highly specialized care (Buttigieg et al., 2018; Cheng et al., 2019). Vicendese et al. (2020) mentioned that some hospital characteristics may influence the length of stay (LOS) and may predict the cost of care (Cummins et al., 2019). Little knowledge exists about the correlation between hospital characteristics such as hospital size, discharge volume, location, teaching status, hospital ownership on LOS, and healthcare cost. Understanding the relationship may help hospitals improve strategic planning and adjust business models better suited to increase profits. In addition, the knowledge gained from the study may promote transparency of healthcare costs to assist in future healthcare cost reduction initiatives. However, the HCUP data set has not been applied to examine the relationship between the length of stay, hospital characteristics, and healthcare cost for all patients. Some research exists within specific diagnoses (Cummins et al., 2019; Sarvepalli et al., 2019), but no known study covers all patients.

The purpose of this quantitative correlational study was to examine the relationship between inpatient hospital (a) LOS, (b) hospital characteristics, and (c) cost of care. The independent variables are the LOS and hospital characteristics. The dependent variable is the cost of care. The target population consisted of community hospitals participating in the Nationwide Inpatient Sample (NIS) data collection. The geographical location was the United States. Hospital administrators, healthcare stakeholders, and patients might potentially use the study's findings to choose facilities, negotiate prices, and make better business decisions. The implications for positive social change include understanding the correlation of care cost better, thus shining a light on additional strategies to make healthcare more affordable and accessible to a larger population.

Target Audience

The study's target audience consisted of hospital administrators, payer stakeholders, and patients interested in healthcare cost reduction. Examining the relationship between inpatient hospital LOS, hospital characteristics, and cost of care may lead to cost-saving strategies and organizational profitability that healthcare leaders and stakeholders may be interested in understanding. In addition, patients may find the study educational to recognize correlations between teaching status, location, length of stay, and cost of care to raise further awareness and develop strategize for their choices.

Research Question and Hypotheses

What is the relationship between inpatient hospital length of stay, hospital characteristics, and cost of care?

Null hypothesis (H_0): There is no statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

The alternative hypothesis (H_1): There is a statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

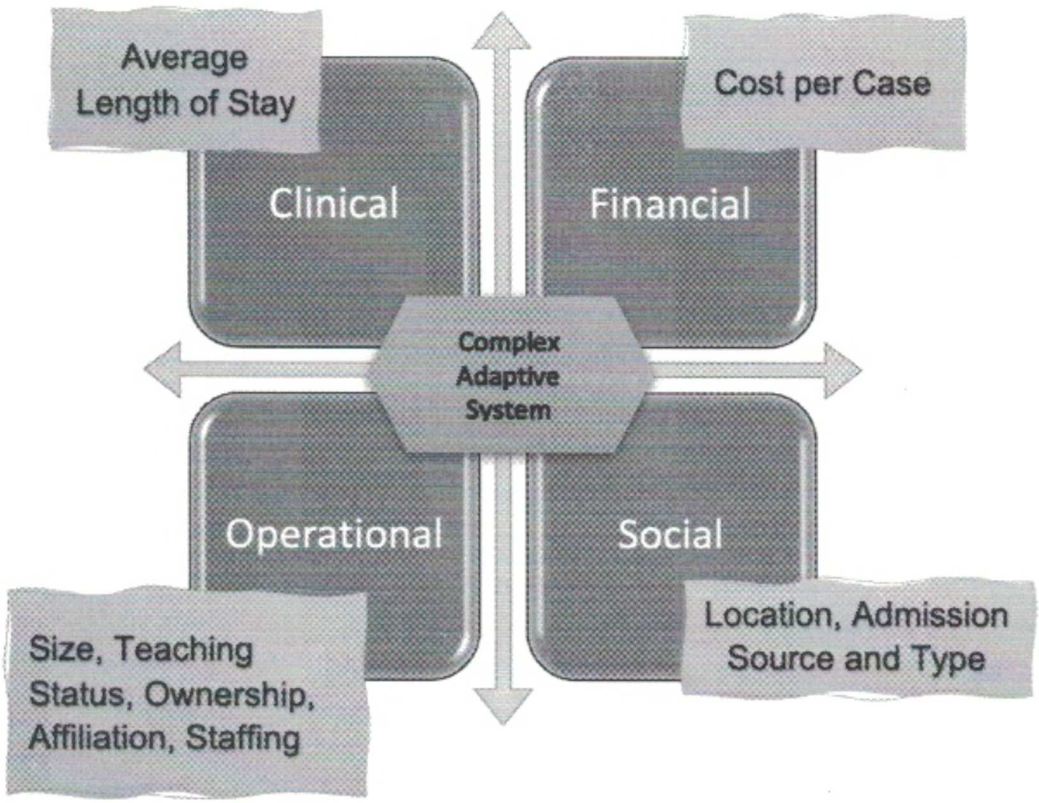
Theoretical Framework

Within my study, I employed the CAS theory founded by Holland (1995). According to Hodiamont et al. (2019), the CAS theory is not grounded in a specific discipline allowing me to apply it in various domains: clinical, operational, social, and financial. Ellis et al. (2017) described CAS as a nonlinear, self-organized, relationship-based, and adaptable system. The researchers suggested that CAS theory has significant implications for organizational development and system design, particularly in too complex social networks such as healthcare, where complexity has skyrocketed in the past decade (Bourgeault, 2019; Glover et al., 2020; Sivakumar et al., 2018). The CAS approach to review the healthcare system helped me to understand the relationships between clinical, social, operational, and financial networks, as shown in Figure 1.

Following CAS theory had proven to be robust for exploring relationships among interdependent variables. Many researchers found CAS applicable and relevant to various hospital settings where interactions may result in unintended results or unexpected behaviors (Burrows et al., 2020; Olsson et al., 2020; Stark, 2020). Healthcare costs within CAS require healthcare leaders to be sensitive to small changes within systems that influence prices like LOS, staffing, admission source, and type. Buttigieg et al. (2018) described hospital characteristics, processes, and hospital team relations that affect LOS or patient days spend at the hospital. The author shared that LOS is one of the indicators broadly used in developed countries to assess efficiency to control healthcare costs (Buttigieg et al., 2018). The researchers suggested that utilization of the CAS may promote evidence-based strategic actions for healthcare leaders where staffing and patient perception are the variables that leaders keep track of daily (Reed et al., 2019; Martin, 2018; Penney et al., 2018). Thus, making proposed variables the best choice for my study to examine the relationship following CAS's theoretical framework.

Figure 1

Theoretical Framework: The Relationship Between Systems



Source: Author’s summary based on literature review

Significance of the Study

Healthcare experts are continuously looking for strategies to decrease U.S. healthcare expenditures, where hospital care was one-third of the cost in 2016 (Dalen et al., 2018). Community hospitals carry responsibility to ensure patients are appropriately admitted and cared for with an optimal length of stay. Healthcare leaders will benefit from this quantitative correlational study with a continually changing environment to better understand what influences patients to remain at the hospital. Healthcare leaders could also use the study results to allocate limited resources, promoting hospital efficiency, and maximizing profitability. It may stimulate the coordination models' re-engineering or even influence health policies to cover better community care hospital resources. Patients may find the study beneficial to guide them choosing the right facility of their choice for their healthcare needs.

Contribution to Business Practice

The result of this study may add value to healthcare stakeholders because examining the relationship between inpatient hospital length of stay, hospital characteristics, and cost of care may contribute to improving hospitals' business operations. Sarvepalli et al. (2019) determined that the hospital's size, hospital location, and teaching status influences LOS, hospital costs, and inpatient mortality. Rosko et al. (2018) concluded that high-efficiency hospitals tend to have lower average prices and higher profit margins. The authors described high-efficiency hospitals as lesser size, nonteaching, system-member, for-profit hospitals. By examining the relationship between inpatient hospital LOS, hospital characteristics, and cost of care, the study will provide the effects of hospital characteristics on business profitability. The results may improve healthcare operations by influencing business strategies. Lastly, it may promote additional thoughts on how to mitigate ongoing raise of healthcare cost and influence payers and policy makers along with healthcare business leaders.

Implications for Social Change

The study's findings will foster positive social change, including increasing knowledge about what is needed to optimize the patients' LOS and improve patient flow and perception in acute care settings (Mazhar et al., 2017). The findings may enhance post hospitalized patients' and employees' health and wellness by optimizing resource utilization within acute care hospitals (Friebel et al., 2018; Markle-Reid et al., 2017; Sabbatini et al., 2019). The results could be used by hospital administrators, insurance companies, and healthcare professionals involved in decision making and policy development to reduce and optimize healthcare costs making medical care more affordable and accessible.

This study's significance and value can influence social change by educating healthcare stakeholders about the impact of LOS and hospital characteristics on healthcare costs. Helping healthcare stakeholders and the public better understand the correlation may impact building additional healthcare facilities making healthcare more accessible. Understanding the relationship between inpatient hospital LOS, hospital characteristics, and cost of care may help healthcare stakeholders promote a decrease in LOS and healthcare costs, making healthcare more affordable. Lowering healthcare costs may lead to an increase in patient compliance with treatments and enable healthier people.

A Review of the Professional and Academic Literature

The purpose of this quantitative correlational study was to examine the relationship between the length of stay, hospital characteristics, and cost of care. The hypothesis was that the linear combinations of the size of stay, and, hospital characteristics may predict the cost of care. Examining the literature allows for a better understanding of the business problem and contributing factors. The literature review includes information on the theoretical framework, variables, and data set.

While completing an extensive review of the literature, I used the following keywords: *healthcare cost, the average length of stay, hospital characteristics, hospital reimbursement, healthcare theories, healthcare outcomes, complex adaptive system theory, cost control, healthcare profitability, hospital admissions, teaching hospitals, for-profit healthcare, and healthcare utilization*. Only the articles directly related to the study were further examined for literature review. Most literature included in the research dates no later than five years to ensure the academic rigor required by Walden University DBA program. I used a combination of research material from Walden University Library databases: ABI/Inform Collection, Academic Search Complete, Business Source Complete, EBSCOHost, ProQuest Central, ProQuest Dissertations & Theses Global, SAGE Research Methods Online, Science Diet, HCUP, HERO, and PubMed.

The organization of the review includes a discussion of the theoretical framework of CAS and its implications with healthcare organizations and the HCUP project. Next, I provide a brief overview of the studies related to utilizing the CAS framework, followed by supportive and alternative theories. The subsequent sections detail the dependent and independent variables, including average length of stay, hospital characteristics, and cost of care in the view of the CAS framework. Finally, the summary of previous correlational and empirical studies describes the business's need to further understand the relationship between recommended variables.

Complex Adaptive Systems Framework

Healthcare today is a complex system that includes care providers, acute, long-term, and supportive care facilities, ambulatory clinics, imaging centers, laboratories, health insurances, controlling agencies, and government oversight. Some researchers consider healthcare extremely complex social network based on structure (Pype, et al., 2018; Valeras 2019). Others like Fylan et al. (2018) looked at complex healthcare system as complex ego-net approaches rather than healthcare policy recommendations or structure. Thus, the theory has significant implications for organizational development and system design, particularly in too complex social networks such as healthcare, where complexity has skyrocketed in the past decade.

The concept of complex adaptive systems in healthcare reached international arena. Literature review shows the utilization of the CAS theoretical framework in Canada, Germany, Belgium, and Australia (Burrows et al., 2020; Ellis et al., 2017; Hodiamont et al., 2019). Stumberg and Bircher (2019) used CAS theory to look at cost reduction in the U.S. Similarly, Stark (2020) reviewed the impact of case management on decreasing LOS in the U.S. In the scope of my study, the U.S. plays a critical role as my work will be based on the secondary data set obtained from U.S. hospitals. Taking into consideration globalization and cultural diversity, I am not surprised researchers view healthcare services through CAS framework.

The CAS has been around for a while in many forms. Systems theory was first mentioned by Scott (1961), followed by Kast and Rosenzweng (1972), who looked at interconnected parts of systems and mentioned healthcare (Scott & Davis, 2016). The CAS theory became more popular in the last several years due to its complexity and interdependency. Peterson et al. (2019) found that the multiteam system lens is the most comprehensive addressing complexity of care coordination frameworks. Glover et al. (2020) examined the relationship between healthcare unit complexity and innovation using CAS theory. Traditional hospitals consist of many departments that interact and collaborate to achieve the common goal of providing patient care. Thus, complex healthcare environment makes the CAS theoretical framework logical and intuitive for implementation in healthcare.

A distinctive feature of CAS is its property of a single model with multiple applications and self-organization. For example, the healthcare participants' care coordination or processes affect each other via feedback mechanisms that react to the environmental and other changes (Penney et al., 2018; Peterson et al., 2019). The elements then self-organize to react and adjust to the situation at hand. Petrie (2018) concluded that healthcare research has moved beyond the complex input-throughput-output model. Multi-application self-organizing flow constructs a foundation to optimize the regulation of CAS characteristics.

CAS theory has several distinctive characteristics. Carmichael and Hadžikadić (2019) described them as having a significant number of self-similar agents that (a) utilize one or more levels of feedback; (b) exhibit emergent properties and self-organization; (c) produce non-linear dynamic behavior. Similarly, Penney et al. (2018) concluded that education and self-organization characterize the CAS framework. Recognition of the multidisciplinary nature of experiences brings together many scholars from different studies to continue applying CAS to a wide variety of research questions.

CAS is applicable to many industries that work with complex, unpredictable, multilayer interactions. Rădulescu et al. (2020) looked at patterns of knowledge with sustainability within a smart city concept using CAS logic. Shiha and Chaczko (2019) used CAS to visualize information, taking into consideration constant change and complexity of the incoming data. You (2021) studied power grid planning in the electricity market environment. All authors identified common characteristics of CAS where nonlinear interacting elements create subsystems. The behavioral, environmental, social, and economical changes impact the variability of subsystem formation. Thus, it alters future outcomes. The composition and relations within the subsystem is essential to fully understand because further interactions may lead to more complexity.

I found CAS theory application in healthcare intuitive. Hospitals consist of many departments that interact and collaborate with internal and external customers and partners to achieve the common goal of providing patient care. Stumberg and Bircher (2019) looked at cost reduction in healthcare using CAS theory. The authors argued that CAS in healthcare allows healthcare workers to fulfill their purpose and drive healthcare costs down. Likewise, Glover et al. (2020) examined the relationship between healthcare unit complexity and innovation using CAS theory. Authors showed that healthcare complexity is associated with better performance and advised that CAS lens view is more unique for healthcare. Both studies described healthcare as complex adaptive system. CAS theory application is in the core of healthcare.

Work processes and roadmaps in hospital settings depend on the clinical standards, socio-economic, and behavioral interactions. According to Penney et al. (2018), interventions designed to decrease the length of stay or increase profitability in the hospital should have characteristics of learning and self-organization to be helpful. Petrie (2018) shared recent changes in the research where the patient flow problem of emergency department transition from simple to complicated to complex. The article has shown that healthcare research has moved beyond the complex input-throughput-output model. Pype et al. (2018) explored the causes of healthcare team behavior and factors influencing learning. First, the authors identified that the healthcare team does not always function as CAS. When there is uncertainty about how to best deal with the situation, thinking outside the box, or trying out new approaches, the team works as a CAS. Procedure and guidelines make the unit operate in a plan-and-control way. Second, the authors identified that the healthcare team is adaptable to the situation and functions on seven principles. They concluded that healthcare teams as CAS might explain different healthcare behavior aspects with implications for education, practice, and research. All of the above examples presented nonlinear flow within organization and team structure. Employees' work processes, education, learning patterns and more impact behavioral interaction can create subsystems affecting healthcare under CAS view.

Framework Relations to Variables

The guiding framework for this study was CAS, which scholars use to explain healthcare organizations. Miller and Page (2007) devoted an entire book to complex adaptive systems where authors review social complexity and dynamics, organizational decision making, computational modeling, and dimensions. Buttigieg et al. (2018) found that healthcare systems' components are associated with CAS. LOS is affected by access and admitting services, date and time of admission, availability of beds, clinical pathways, the efficiency of support services, and transfers between other facilities (Buttigieg et al., 2018; Handel et al., 2018; Youn et al., 2019). The complexity of a geographical area, ownership, teaching status, and size of the facility influence hospital characteristics and, ultimately, cost of care (Freeman et al., 2020; Sarvepalli et al., 2019; Burkle et al., 2018). CAS becomes a DNA for variables within healthcare. Healthcare adapts and thrives based on internal self-learning multidirectional interactions.

Alternative Frameworks

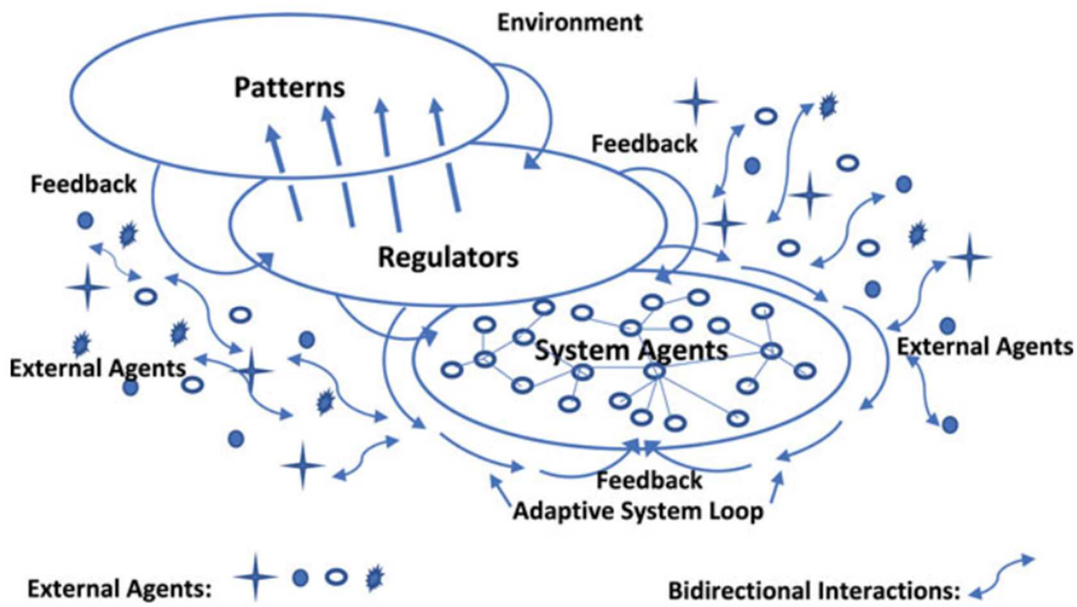
The complexity of healthcare and the constantly changing environment require the framework's flexibility depending on the subject. CAS utilization has been booming in the last decade, along with other theories. Akinleye et al. (2019) looked at healthcare finance under Resource Dependency Theory (RDT). Peterson et al. (2019) found that the multiteam system lens as the most comprehensive one when focused on intensive care units in the hospitals. Freeman et al. (2020) looked at for-profit and non-profit organizations through public choice theory. The authors chose the lenses based on the topic within the question. The constant change does not mean contradiction, it means complexity and transformation under different lights.

The definition of healthcare includes personal beliefs, acceptance in practices, cultural norms, and social determinants. The literature showed the need to better understand the interpretation of health. Dorsey et al. (2020) proposed healthcare as service-based deliveries through a transformative service research perspective, highlighting healthcare and financial considerations. Fylan et al. (2018) followed the Social Network Analysis (SNA) framework to provide practical understanding that described patients as involved agents, healthcare interactions as complex flow within healthcare, and post-discharge challenges. To further understand full complexity of healthcare cost, I will further ensure the inclusion of a suitable data set that shows intended information to show the complexity within the system.

There are some differences and similarities between CAS and alternative frameworks. The authors shared similar thinking that a complex healthcare system consists of complex ego-net approaches rather than healthcare policy recommendations. The studies show that financial health plays a critical aspect of the healthcare system in the overall variability of theoretical lenses. The unique difference of CAS from the alternative theories is the distinctive system-within-a-system concept (Gilman, 2021). Each component integrates and changes the central system based on interactions and learnings with other systems and the environment. The CAS theory evolves and develops integrated alternative theories as it creates bidirectional interactions with all agents as shown in Figure 2.

Figure 2

Theoretical Framework: Integration of CAS



Source: A variation of a CAS model depicting interactions within systems from emerging patterns and respective feedback loops that influence the interactions of agents based on various descriptions of CAS models found in literature (Gilman, 2021).

Secondary Data Set

Do we have a data set that protects against challenges of time, variability of healthcare settings, and complexity? The HCUP is a system of databases that was first developed in 1994 and is sponsored by the Agency for Healthcare Research and Quality (AHRQ)1. First collected in 1988, this family of interrelated databases contains inpatient, outpatient, and emergency department patient information updated annually. The HCUP project collects patient data gathered by state, hospitals, associations, and the federal government. Sarvepalli et al. (2019) found that HCUP data set was the right one to examine national inpatient discharges related to the diagnosis of gastric cancer. Others have followed the lead of Hellinger (2004) and focused on different types of variables that are readily available within the HCUP data set. Long time collection of variety of data points made the HCUP project the most extensive collection of multi-year health care data in the United States.

The HCUP databases have been a powerful resource for many projects. Cummins et al. (2019) analyzed pediatric patients and looked at hospital characteristics impact on the cost and LOS. Rosko et al. (2018) compared performance, operating characteristics, and market environment of high and low-efficiency hospitals among 37 states. Similarly, Wani et al. (2019) reviewed the 2014 Nationwide Readmission Database to review 30-day readmission for psychotic disorders (SPDs). Cook and Averett (2020) looked at upcoding challenges using the dataset. The HCUP databases collect state data, hospital associations, private data organizations, and the Federal government making it robust in national trends review.

Researchers view national trends in healthcare utilizing different types of datasets. Shafiq et al. (2020) looked at the length of stay (LOS) using the HCUP dataset. Similiarly, Turbow et al. (2021) examined the LOS, cost, and in-hospital mortality using HCUP data. Although the HCUP data has many points for review, it is not the only data set available. Burkle et al. (2018) looked at the LOS and cost using the AHA Annual Survey and a Medicare impact file. Lim et al. (2019) used the Premier Perspective Database of US hospitals' discharge admissions records to review hospital characteristics. I found the HCUP set with the information to help me find the answer to my research topic. Different databases help researchers better understand the relations between variables and promote unbiased views on national trends.

The HCUP data is divided into national and state databases, and each serves specific goal helping to answer variety of questions. Turbow et al. (2021) examined the NRD data set within the HCUP project to review fragmented admissions. Spitzer et al. (2019) reviewed the HCUP national data set to review readmission risks and costs. Both studies have one mission looking for ways to decrease healthcare costs. The HCUP data sets provides a large volume of information being readily available for downloading and processing. I will use NIS data set to complete my research.

The Nationwide Inpatient Sample (NIS) is the most extensive database within the HCUP. It provides inpatient information from over 1100 hospitals in the U.S. Utilization of this database allows researchers to compare HCUP inpatient data to other databases to provide a national representation of the status of healthcare quality. Admon et al. (2019) completed retrospective, repeat cross-sectional analysis using 2004-2015 data from NIS compiled by HCUP. The authors reviewed the incidence of hospital deliveries related to maternal acetaminophen or opioid use with weighted logistic regression. In addition, they measured clinical outcomes and costs with weighted multivariable logistic regression and generalized linear models. Researchers use the NIS data set to explore relations between categories and advance knowledge in variables.

NIS data contains several hospital characteristics and carries several limitations. Various data points allow to examine qualitative and financial impact; however, it does not cover causation as the data set does not go beyond discharge (Robb et al., 2019).

Cook and Averett (2020) completed an examination of HCUP survey data from 2005 to 2010 to review if hospitals up code the data to increase reimbursements due to recent changes in the severity of the cases. NIS data provides a great perspective into healthcare analytics, additionally, we have more options to learn from different angles.

Alternative data may be obtained from various sources. Chen et al. (2019) looked at the National Health Research Database during his healthcare cost analysis. Wickle et al. (2021) used data provided by insurance companies to review healthcare costs, and preventable measures currently not fully implemented within the U.S. Sabbatini et al. (2019) obtained data utilizing Truven Health Analytics MarketScan Commercial Claims and Encounters. Lim et al. (2019) reviewed economics using the Premier Perspective database of U.S. hospital discharge records. All authors looked at secondary data to scan and analyze trends related to healthcare cost, length of stay, and impact on profitability.

The benefits of HCUP data are a large volume of records. NIS is the largest publicly available, all-payer, inpatient database in the USA. The data set contains clinical and non-clinical data elements with weights assigned for national averages. With the rapid healthcare shift to value-based care, the HCUP data set provides a large amount of information to help hospitals look for new ways to improve quality without unnecessarily increasing the maintenance cost and for patients' healthcare payers to make better decisions facilities partner up with. Cook and Averett (2020) completed an examination of the Healthcare Cost Utilization Project (HCUP) survey data from 2005 to 2010 to review if hospitals up code the data to increase reimbursements due to recent changes in the severity of the cases. Cook and Averett (2020) concluded that there is statistically significant and economically meaningful upcoding. The authors were convinced that there were about 20 million dollars in excess due to upcoding in 2008. Chinta et al. (2019) reviewed hospital charges using the HCUP NIS data set and advocated for insurance companies and hospitals to look at strategies focused on regions and LOS.

The HCUP data set has limiting factors leading to potential inaccuracy of the information. According to Cummins et al. (2019), the data did not contain an understanding of the cases, leaving results open to interpretation. Technological advancement and new programs within each facility may influence how they are treated and coded in the system. Sarvepalli et al. (2019) argued that with any changes in hospital characteristics learning curves may affect the variation in interpretation of the results. The authors did not discuss the theory for the study nor covered the clinical side of the course. Both authors did not have a clinical background leading me to believe that they operated based on number interpretation that may not always be accurate or effective.

The HCUP data requires additional research. Farley et al. (2020) completed a retrospective cohort study to examine differences between in-hospital mortality groups treated in rural, urban-teaching, and urban-non-teaching hospitals as well as public and private hospitals. The data set was obtained from the HCUP NIS project. The results concluded that the mortality rate was 14.6% higher in rural hospitals compared to urban/nonteaching centers. The authors recommended continuing research comparing hospital characteristics to mitigate findings.

Independent variable A - Average Length of Stay

The hospital admission rate is on the rise. For 2015 the Centers for Diseases Control and Preventions estimated nearly 30 million ED visits with a hospital admission rate of 10.4% compared to 12.4% in 2018. (CDC, 2015; CDC, 2018). Salway et al., 2017 shared that ED admissions were not always effective or efficient where patients are subjected to unnecessary inpatient admissions when hospital occupancy is low. The opposite happened when hospitals did not admit a substantial percentage of patients requiring inpatient care during high occupancy times. As a result, the cost of care continues to grow. The Centers for Medicare and Medicaid Services (2008) no longer pays health care organizations to treat infections or injuries that occur in the hospital due to inadequate or improper patient care. Stark (2020) completed a study examining effective case management workflow to review timely patient dispositions. Stark (2020) concluded that increasing the skill level of case managers promotes early recognition of discharge barriers and decreases avoidable days, promoting healthcare costs.

Logically increased LOS creates more opportunities for hospital-acquired complications. In addition, optimizing the length of stay promotes the organization's financial stability. Still, it also creates better efficiency and additional capacity without decreasing mortality and impacting the community's life one person at a time. Sarvepalli et al. (2019) examined NIS data to see how characteristics such as location, teaching status, and hospital size influenced LOS through multivariate analysis. The authors reviewed a total of 679,330 hospital discharges with the principal diagnosis of gastric cancer. Sarvepalli et al. found that hospital stays increased by approximately 340 stays per year (±110; $P=0.00079$). However, inpatient mortality rate and LOS declined by 0.36% per year (±0.024%; $P<0.0001$) and 0.11 days per year (±0.01; $P<0.0001$), respectively. The inpatient charges have increased at the rate of $3241 per year (±133.3; $P<0.0001$). Sarvepalli et al. concluded that patients with gastric cancer admitted to urban teaching and more extensive facilities had longer LOS than those admitted to non-urban education and smaller hospitals. Patients admitted to urban, teaching, and larger hospitals accrued larger bills than patients who went to small non-urban teaching facilities. Unfortunately, the findings were specific to patients with gastric cancer and not generalizable to all patients.

Many organizations strive to decrease LOS in acute care settings. Odom et al. (2018) used a multidisciplinary team approach to improve patient progression. Key performance indicators included ED LOS, ED LWBS, and M.D. admission order to inpatient bed assigned. The authors reviewed barriers and created action plans to improve patients' flow and ultimately decrease LOS. Following the CAS theory, the authors developed a multidisciplinary team and promoted a review of a variety of metrics. Odom et al. (2018) were successful in describing the complexity of hospital operation. Still, there was no data to review the impact and eliminate the association of the results with other systems within the hospital. Destino et al. (2019) reviewed the data measuring percentages of earlier releases, median wait times for an inpatient bed from E.D., average PACU wait time, discharge satisfaction, seven-day readmission rate, and LOS. Destino et al. (2019) concluded that multimodal interventions to increase discharges before 11 am positively impacted E.D. and PACU wait times. In addition, the authors found a significant correlation with LOS. Due to complexity of healthcare not all the initiatives may be repeated at all facilities with desired outcomes.

The time spent in the hospital is almost a universal indicator of hospital efficiency. Researchers in Australia completed an additive quantile regression model to isolate hospital contextual effects to compare hospital operational efficiencies regarding LOS. The authors reviewed admissions between 2005 and 2015 involving 28,343 cases. They adjusted the model for various patient and hospital factors that may confound the association between provider volume and LOS. Some of the elements included sex, age, admission type, and hospital location. They did not predict efficiency by provider volume; however, the results indicated that all categorical variables were associated with LOS and annual volume. In addition, the authors found that higher yearly surgery volume was associated with lower LOS. Vicendese et al. (2020) indicated that all hospital characteristics might be necessary for predicting LOS except co-location status.

Following CAS theory, LOS can be influenced by many aspects of healthcare flow. From hospital characteristics (Cummins et al., 2019), clinical complications (Lim et al., 2019), staff education, and skillset (Stark, 2020) to operational challenges. Buttigieg et al. (2018) completed a scoping literature review to examine what affects patients' LOS within tertiary-level health care. Donabedian's model included 46 articles to find the following characteristics: healthcare systems, patients, and social/family. The authors found that healthcare systems' components are associated with CAS, where LOS is affected by access and admitting services, date and time of admission, availability of beds, clinical pathways, the efficiency of support services, and transfers between other facilities. Other variables included in the process included professional groups and behavior, communication and multidisciplinary approach, discharge planning, leadership, and knowledge transfer. The authors concluded that hospitals are indeed complex systems that needed to adapt to various emerging challenges.

Considering the complexity of human behavior, some may find it interesting to see how it affects LOS during the holiday season. Lenti et al. (2020) completed a longitudinal exploratory study to review the length of stay for the patients admitted in the December holiday period. The authors reviewed 227 consecutive adult patients in 2017-2019, and theorized that staffing challenges, fragmented care, and system overload might extend hospital LOS. In reviewing clinical complexity, LOS, and early mortality rate, the authors concluded that patients showed a longer length of stay and higher in-hospital mortality during the holiday season. Although the authors did not directly share findings related to understaffing, they selected the timeframe associated with low staffing times, indirectly creating a correlation to the staffing concerns.

Researchers have many attempts to review LOS and healthcare cost. Shafiq et al. (2020) completed a study utilizing HCUP data set to review national trends in healthcare utilization and outcomes among hospitalized patients. The authors concluded that inpatient LOS reduced substantially, but it remained a considerable burden to healthcare costs. The authors concluded that the cost of healthcare continues to rise regardless of LOS reduction. On the other hand, Turbow et al.'s (2021) study shined some light on increasing healthcare costs and impacts LOS indirect pricing when the authors examined the association between interhospital care fragmentation and in-hospital mortality LOS cost in adult patients with 30-day readmissions across critical categories. The authors concluded that LOS was up the whole day longer and more than $6000 more in charge. COPD had no statistically significant differences in LOS and cost. CHF patients had increase LOS by half a day and an increase in price by an average of $2600.

Independent variables B - Hospital Characteristics

Hospitals can be characterized by size, geographic location, funding, ownership, and other characteristics that make hospitals unique in performance and financial success. According to the CAS framework, the differences may be notable, however, interconnected with the operation, cost assurance, and profitability. Studies review the impact of hospital characteristics on performance, quality, and finance.

Bed size of the hospital. In a review of the cost, HCUP data used widely. Some searchers used HCUP data to look at the size of the healthcare facilities. Cummins et al. (2019) found that the cost was lower in large and medium hospitals. Teaching hospitals tend to have less expensive care nonteaching counterparts. Patients who have income in the lowest quartiles are associated with less expensive care. Thus, the authors concluded that hospital characteristics and patient income influence treatment cost, LOS, and surgery type. The authors recommended using a multivariable linear regression model using the HCUP database to analyze further the factors influencing price and LOS.

Wani et al. (2019) reviewed the 2014 Nationwide Readmission Database to review 30-day readmission for psychotic disorders (SPDs). NRD is another system data set within the HCUP project that includes hospital characteristics that researchers may use as an alternative to NIS as they look at the impact of hospital characteristics within healthcare. The authors concluded that hospitalizations were more likely to result in readmissions for younger male patients living in a low-income neighborhood with prior short stays. In addition, the index of admissions was higher for private for-profit, nonteaching hospitals in large metropolitan areas.

Location/teaching status of the hospital. Hospitals varies based on the location/teaching status. Burkle et al. (2018) reviewed how teaching status has a significant impact on the outcome. The policy shall steer less acute patients to teaching facilities as a preventative measure, which will decrease the cost of care in the long term. They concluded that teaching hospitals show lower mortality rates. Moreover, healthier patients seemed to benefit the moistest from the care at teaching facilities leading to decrease healthcare costs in the long term and act as preventative medicine.

One study investigated hospitals by location (Brenden et al., 2020). Caudill et al. (2019) analyzed hospital characteristics' impact on healthcare costs. The hospital's teaching status associated with more risk leads to additional charges to mitigate the risks and more benefits in caring for a high-risk population. Heath et al. (2021) completed a review of the relationship between hospital characteristics and specific types of HIPAA breaches. Heath et al. (2021) concluded that system and teaching hospitals are shown to be at greater risk for violations due to improper disposal. Thus, teaching hospitals have increased operational expenses and costs related to the mitigation of concerns. The authors looked at the hacking and HIPAA problem through the sociotechnical systems theory, which understands interconnections between the parts of the system.

Another negative financial impact of teaching status is in efficiency and operational flow. Rosko et al. (2018) compared performance, operating characteristics, and market environment of high and low-efficiency hospitals among 37 states between 2006 and 2010. The authors obtained data from the Healthcare Cost Utilization Project and analyzed it using Stochastic Frontier Analysis. The authors found that high-efficient hospitals are nonteaching, part of the more extensive system, and for-profit organizations. They do not have quality or safety compromised for efficiency.

Region of hospitals. Hospital region stratified may show practice patterns variations by region. In previous research, there are differences in LOS between east and west coast hospitals. Also, healthcare prices vary from region to region. Cooper et al. (2019) showed hospital price variation based on the areas. Popescu et al. (2019) attempted to compare safety net hospitals by the region looking at HCUP data. The authors showed that the Northeast region has the least number of safety net hospitals closely followed by the west region. Limited information is known about the area of the hospital's impact on the healthcare patterns. The gap suggests the need for further research and exploration of any designs.

Control and ownership of hospitals. Hospital size is not always reflecting the capacity. Structural capacity may be complicated by teaching affiliation, rural or urban spacing of the buildings, and government or private ownership. Since healthcare outcomes markedly vary amongst patients across the hospital settings, inpatient settings have not been intensely studied.

O' Hanlon et al. (2019) examined the relationship between hospital affiliation and performance, comparing hospitals in 2008 and 2017 pre- and post-affiliation. The financial survival of any organization relates to profitability. As a result, many for-profit entities tend to make choices to maximize the margin closing rural and not profitable hospitals. As O' Hanlon et al. (2019) shared, there were no inpatient experience changes, readmission, and E.D. visits between affiliation and nonaffiliated hospitals. Following health system affiliation, rural hospitals significantly reduce diagnostic and imaging technologies, obstetrics and primary care services, outpatient non-emergency visits, and increased operating margins. Thus, the hospitals frequently close the business in rural areas.

Freeman et al. (2020) looked at for-profit and nonprofit organizations to review and compare operational efficiency. Through quantitative meta-analysis, the authors looked at which organization more technically efficient and how it changed over time. The authors did not look at the findings through CAS theory and did not include government-owned healthcare and other facility types. Also, it seemed that the data collection time frame might be misaligned due to assumed calculated year differences. Through lenses congruent with public choice theory, the authors noted that lately, nonprofits be more efficient than for-profit healthcare organizations.

Caudill et al. (2019) analyzed hospital characteristics' impact on healthcare costs. The authors reviewed the correlation between hospital characteristics and blood draw, CAT scan, and EKG services using data from the Medicare database. Completing the decomposition of the cost differences based on the hospital ownership, Caudill et al.

(2019) concluded that costs positively correlate to procedure charges across the ownership types. Although the author did not include evolutions such as teaching and nonteaching, hospital region, and hospital size, he shed light on the potential opportunity to review system membership to decrease operational costs for smaller hospitals.

Dependent Variable – Cost of Care

I focus my research on healthcare costs within the hospital's acute care setting because the extended hospital stay is the most significant component of medical expenses (Cheng, Wang, & Ko, 2019). The cost goes beyond a dollar sign. It has something no one can measure:

- spending an extra day with grandchildren
- attending a wedding
- holding a newborn at home
- celebrating a birthday with the family
- having a fresh gap of air or a touch of sunlight

These we cannot measure, but healthcare environment unintentionally may prolong the stay of patients in a facility. My doctoral work will advocate for patients by shining light on relationships between variables and fulfilling the knowledge gap. A better understanding may lead to potential strategies healthcare stakeholders could implement to improve patient flow. With my work, I will shine a light and open conversations for future research that can further investigate the cause and effect of rising healthcare costs reaching 3.5 trillion dollars in 2017 (CMS, 2018).

The U.S. healthcare cost continues to be on the rise. Experts are looking for ways to decrease it to make healthcare more affordable, accessible, and equitable. Crowley et al. (2020) shared that the United States spends far more than sister countries. The author convinced that many Americans could not afford health insurance. The U.S. is the only wealthy industrialized nation without universal health coverage (Crowley et al., 2020). Similarly, Cooper et al. (2019) found it alarming when the inpatient hospital price increased at a disproportional rate of 42% between 2007 and 2014. The Healthcare Cost Institute reported that spending per hospitalization increased by 16% with the price increase in all admission categories. (Healthcare Cost Institute, 2017). Many factors add to the big picture: staffing, admission processes, payers, and pharmacology.

In a complex hospital environment, many factors influence the financial success of the organization. Staffing plays a vital role in profit margins for hospitals. Oppel and Young (2018) found that all staffing variables were significantly associated with patient experience. Moreover, teaching hospitals are perceived to have better staffing leading to better reimbursement. Similarly, Epané et al. (2019) concluded that hospitals received a marginally significant increase in operating profitability well-staffed by hospitalists. A great example of staffing impact on performance is the holiday season, where hospitals are stressed to ensure coverage. Lento et al. (2020) concluded that patients showed a more extended stay during the December holidays and higher in-hospital mortality. Thus, staffing effectiveness influences patient perception, hospitals' reimbursement rates, and profitability.

The authors completed an exploratory, multiple-case study to examine Physician Assistant integration in various healthcare settings. Like my future study, the authors followed the CAS framework and conducted interviews with 46 healthcare providers and administrators across 13 hospitals and six clinics in Ontario, Canada. The authors conducted interviews, reviewed processes, site specific documents. They analyzed data in 3 phases and found that P.A. increases patient access to care and helps improving patient flow. There are some limitations to the study, including the variability of CAS principles that may lead to conceptual confusion. In addition, the authors exclusively focused on settings where P.A. role integration was successful.

The article was valuable to my study as a review of the cost-cutting tactic that some of the sites might use to improve patient flow/efficiency and address some staffing challenges within physician groups. In addition, the analysis of the study through CAS lenses helped me understand the author's considerations when the CAS framework was used in research settings. Finally, although the article has some limitations and was conducted outside of the U.S., the information may apply to the U.S. practices as we have active P.A. roles in our healthcare environment.

Healthcare business leaders must be creative in identifying ways to decrease healthcare costs and the utilization of medical services. Delling et al. (2019) looked at the effect of cannabis legalization on health effects and healthcare utilization in Colorado, comparing the state with New York and Oklahoma. Using the HCUP data set, the authors looked at hospitalization rates over three states and concluded an overall neutral effect. Although the chronic pain admissions decreased, the cost was offset by increased hospitalizations due to overdose, MVAs, and overdose injuries. Utilizing HCUP data set helped better understand the opportunities looking through diverse angles of the concerns for healthcare cost.

Payers play a crucial role in identifying the healthcare cost. Cai et al. (2020) examined how the payer approach may impact healthcare costs. They identified 22 single-payer plans over the past 30 years. The authors conducted a systematic literature review analyzing literature between June 1 and December 31, 2018. They found that 86% of the analyses would fail in the first year and predicted savings from simplified billing and lower drug cost. They concluded that there was a near-consensus that single-payer would reduce health expenditure while providing high-quality insurance to all U.S. residents.

Wickle et al. (2021) looked at preventable ways to decrease the cost in the long run by improving care coordination. The authors concluded that study group participants consulted cardiologists more frequently; however, healthcare cost savings were due to the lower cost of cardiovascular hospitalizations and lower costs of pharmacotherapy prescribed by cardiologists.

Because of the complexity of healthcare, many variables may impact the cost. Turbow et al. (2021) examined the association between interhospital care fragmentation, in-hospital mortality, LOS, and cost in adult patients with 30-day readmissions across critical categories. The authors concluded that with some diagnoses like myocardial infarction, the cost of care is highly impacted by fragmented admissions.

The literature review would not be complete without a glance into healthcare cost policies. Stadhouders et al. (2019) examined policy effectiveness using total payer expenditure as a primary outcome measure. The authors found no evidence for over 50% of significant groups of cost-containment policies. As a result, the recommendation was to frequently evaluate policies with high-quality evidence to support cost-sharing, managed care competition, reference pricing, generic subscription, and tort reform.

Hospital governance may impact how decisions are made and implemented within the facility. Dixit (2020) reviewed hospital governance structure on healthcare cost and operational effectiveness. The authors' recommendations to continue research in healthcare cost, value, and healthcare structure support the need for my study and identify the gap in the literature that I plan to address in my work.

Rosenberg et al. (2018) reviewed healthcare costs in the example of medication pricing. The study described the association of pricing and what influences the charge with increased demand and limited competition. The way medication is priced today may affect how patients or payers get charged to recoup the spending and increase margin. It may further increase the cost of care as a bottom-line effect. The authors concluded that the price of naloxone outpaced overall inflation, increasing across nearly all formulations. They explained it by external shocks (raw material prices, supply disruptions, increased demand) and limited competition. With a limited number of naloxone producers, the cost increases as leverage to control the prices remain with a limited number of manufacturers.

Healthcare Profitability

No margin, no mission. The business side of hospital healthcare characterized by two main factors providing healthcare services and receiving profits. Operating margin is frequently a measure of profitability in assessing the impact of hospitalist staffing. Staffing intensity matters as it drives an increase in operational efficiency, employee engagement, decrease in LOS, and a marginally significant increase in operating profitability (Epane et al., 2019). Other drivers included hospitals' desire to reduce LOS and align physicians to hospitals' strategies.

Healthcare facilities constantly in search of strategies to improve profitability and increase margins. Hallam and Contereras (2018) followed lean methodology and Toyota Production System tools and techniques to examine 23 Baldrige award winners and set them for success. The authors noted that 83% of the companies implemented lean in many areas, including cost, quality, waste reduction, lead time, and efficiency. Coincidently, 83% reported an increase in profits.

Hospital financial performance plays a vital role in the ability of the organization to provide and grow service lines. Moreover, Akinleye et al. (2019) showed a correlation between hospital financial performance and quality and safety of patient care. The authors reviewed 46 indicators, including financial performance and quality and patient safety indicators. The authors concluded that financially stable hospitals have better patient experience, lower readmission rates, and decreased risk of adverse patient quality and safety outcomes for medical and surgical patients. As a complex adaptive system theory suggests, the researchers shall review multiple co-variables within the study. The healthcare system is complex and relationship-based with interrelated agents and processes. Bichescu et al. (2018) completed panel data regression models to analyze clinical, operational, and financial performance data for 288 acute care hospitals from California for the period spanning 2004-2011. The authors concentrated on three independent variables: cost per discharge (CPD), the average length of stay (ALOS), conformance quality (ConfQual) to assess changes in hospitals of process excellence. In addition, they investigated the association between process excellence and overall hospital performance measures, including market share and profitability. The authors concluded that profitability has a strong relationship with process excellence metrics where lower LOS and CPD are associated with increased hospital market share and increased hospital profitability

Transition

Section 1 was an introduction of the study and an overview of the healthcare cost. I included the historical background of the study, the problem and purpose statement, and research questions. To meet secondary data analysis rubric, I also included the significance and theoretical framework followed by the literature review. In problem statement I raised concern about the correlation between hospital characteristics such as hospitals' size, discharge volume, location, teaching status, hospital ownership on LOS, and healthcare cost. Understanding the relationship may help hospitals improve strategic planning and adjust business models better suited to increase profits.

In Section 2 I will reinforce the purpose of the research and will cover the study method and design as well as discuss the secondary data set that I will use in the study. In depth data collection information such as HCUP instruments.

Section 2: The Project

In this secondary data analysis quantitative study, I examined the relationship between the variables. Section 2 covers the methodology, design, and research elements of the study. In section two, I also review multiple regression assumptions and the steps to mitigate them. The section concludes with a discussion of the validity of data.

Purpose Statement

The purpose of this quantitative correlational study was to examine the relationship between inpatient hospital (a) LOS, (b) hospital characteristics, and (c) cost of care. The independent variables are the LOS and hospital characteristics. The dependent variable is the cost of care. The target population will consist of community hospitals participating in the Nationwide Inpatient Sample (NIS) data collection. The geographical location was the United States

The secondary data analysis reviewed data accessible to the public from Healthcare Utilization Project (HCUP). The purpose of this quantitative correlational study examines the relationship between inpatient hospital (a) LOS, (b) hospital characteristics, and (c) cost of care. The independent variables will be the LOS and hospital characteristics. The research question was: What is the relationship between inpatient hospital length of stay, hospital characteristics, and cost of care? I will investigate two hypotheses:

Null hypothesis (H_0): There is no statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

The alternative hypothesis (H_1): There is a statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

Research Method

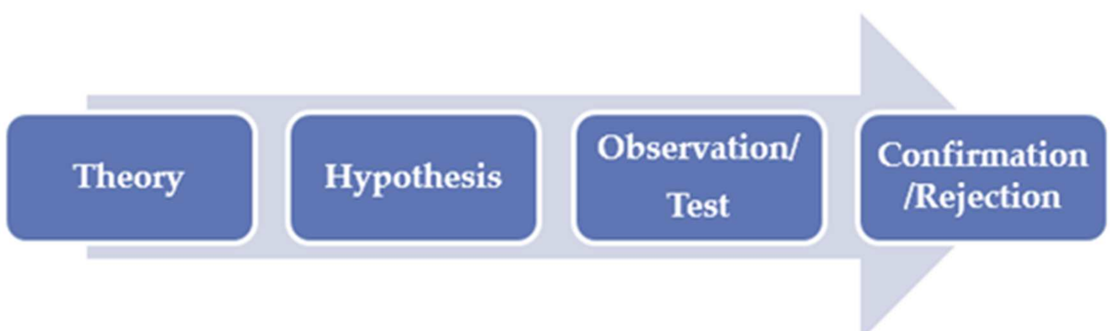
Quantitative research is a scientific way to align theoretical concepts with variables. Quantitative research methods allow business leaders to project future business conditions helping them to adjust business strategies as needed. With a current economy and existing research, business leaders can make it work to their advantage by promoting flexibility, fluidity, and system thinking (Millar, Groth, & Mahon, 2018). The focus of quantitative research is to generate knowledge and create an understanding of a phenomenon, its frequency of occurrence, magnitude, and effects on the sample population. Knowledge of quantitative techniques helps researchers to show the angle needed to determine the impact.

There are advantages and disadvantages to the quantitative methods of research. First, quantitative research investigates the answers in numerical measurements, separating the social behaviors into statistical frequency or rate (Rahman, 2020). Second, it allows researchers to process extensive information and represent findings in a larger sample size, making the research truth worthy. Lastly, data analysis is less time-consuming as more statistical software is available for data processing, such as SPSS, Minitab, Stata. However, there are disadvantages as well. Rahman (2020) found that the quantitative approach takes a snapshot of a phenomenon measuring variables at a specific moment in time. It may lead to the results being taken out of the context or readers not getting deeper underlying meaning and explanations.

I considered qualitative and mixed methods but decided to complete quantitative research because in addition to advantages mentioned above, it entails a deductive approach where researchers look at data to examine a theory. It is frequently associated with positivism and the scientific method to measure the statistical significance of findings (Ary, Jacobs, & Razavieh, 2018). Deduction starts with an anticipated logical pattern that I can test against observations. It explores a real phenomenon or a theory further, testing and validating it under various circumstances. Theory plays an essential role as it creates a basis for the deductive approach. The deduction flow chart as shown in Figure 3 from www.reserch-methodology.net helped me visually understand the role theory plays in deductive reasoning. I see it as a core of the research where theory is created to explain, predict, and understand. In some cases, the researcher can challenge and extend existing knowledge within the limits of assumptions (Abend, 2008).

Figure 3

Deduction Flow



Source: Obtained from www.reserch-methodology.net

With the help of the CAS theoretical framework, I looked for data helping to answer my research question: What is the relationship between inpatient hospital length of stay, hospital characteristics, and cost of care?

The null and alternative hypotheses are as follows:

Null Hypothesis (H_0): There is no statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

Alternative Hypothesis (H_1): There is a statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

There are disadvantages to qualitative and mixed methods. The data collected may originate from personal perceptions and opinions. With qualitative research, there is a higher chance for personal bias. Recognizing personal bias, either excitement or passion towards the topic and dislike of certain participants, may mislead the findings (Yuan, Tian, Huang, Fan, & Wei, 2019). We create a bias about ourselves based on what we see in our interviews (Cronin, Craig, & Lipp, 2019). Healthcare cost is better suited to be reviewed in numbers and via quantitative method to avoid biases. Mixed methods contain qualitative and quantitative methods of data collection. Therefore, the mixed methodology did not support the purpose of the study either.

Research Design

I followed an ex post facto correlational study design for the study design. I will review a relationship between inpatient hospital length of stay, hospital characteristics, and cost of care. According to Saunders et al. (2016), the correlational design addresses a specific business problem where descriptive statistics promotes describing variables numerically. Other study designs are less optimal to achieve my goals within the provided timeframe of my work while numerically describing the correlation between variables.

The population was a sample of discharge records from all HCUP-participating hospitals. According to HCUP NIS description of data elements (2018), not all data elements are available from every state, available each year, and uniformly coded across States. I examined the data obtained for missing data before analysis and remove incomplete data points. According to Cohen (2009), discarding data with at least one variable value missing is acceptable until the statistical power is diminished. I followed the appropriate sample size identified with power analysis to show the strength and power of variable relationships by randomly selecting 300 hospitals to equally represent different regions, teaching status, hospital size, control/ownership.

Correlation shows a relationship between two variables, and causation implies direct or indirect cause. A correlation expresses the strength of linkage or co-occurrence between two variables in a single value between -1 and +1. It is limited to linear relationships between variables (Green & Salkind, 2017). Even if the correlation coefficient is zero, a non-linear relationship might exist. Bivariate correlation shows the effect of two or more variables. We can visualize the relationship between two or more variables on a scatter plot to help verify that the variables have a linear relationship.

Ex post facto research has its advantages and disadvantages. On the one hand, Simon and Goes (2013) found ex post facto research more suitable when conducting social studies within healthcare where there is no need to influence the characteristics of human participants. However, there is challenging to understand the foundation of the conclusion from the evidence collected. I will look for assurance that the data is collected equally between the hospitals participating in HCUP projects and any differences found during the data collection steps (Allen, 2017). I will address the challenges with the ex post facto design through my expertise and experience in healthcare and by better understating the data set used during my study.

Reliability is the main quality criteria of an instrument. It is the ability to reproduce a consistent result in time and space or by different observers, showing aspects of coherence, stability, equivalence, and homogeneity (Tang, 2015). Yin (2018) defined reliability as the possibility to repeat a study with a similar result. Reliability is not a fixed property. I plan to improve reliability by making sure the data is accurate and relevant to my research study.

A faulty unit of analysis may skew the research leading to false conclusions and negatively impacting business performance. Misrepresentations of data lead to confusion for researchers and overall readers. Unit of analysis depends on a research problem, stated Kumar (2018). The author shared that unit of analysis answers the question of ‘what’ and ‘how.’ In a quantitative case study, the researchers may examine the relationship between variables where the data collection unit may be an individual variable, person, hospital, or hospital outcome. In my study, the unit of analysis is a hospital. I look at the potential relationship between the average length of stay, hospital characteristics, and cost of care in acute care hospitals in the U.S.

Buttigieg et al. (2018) found that LOS is one of the key performance indicators that help researchers improve quality and enhance hospitals' performance. Rosko et al. (2018) shared that hospital characteristics contribute to efficiency in hospital operations. Thus, making the variables an excellent choice for the study, as shown in Table 1.

Table 1

Chart of Variables

HCUP Data Element	**Description**	**Value/Description**	**Scale of Measurement**
HOSP_BEDSIZE	Bedsize of Hospital	1-Small; 2-Medium; 3-Large	Ordinal
HOSP_LOCTEACH	Location/teaching status of a hospital	1-Rural 2-Urban nonteaching 3-Urban teaching	Nominal
HOSP_REGION	Region of hospital	1-Northeast 2-Midwest 3-South 4-West	Nominal
H_CONTRL	Control/ownership of a hospital	1-Government/nonfederal; 2-Private/not-for-profit; 3-Private/invest-own	Nominal
LOS	Length of stay, cleaned	0-365 days	Ratio
TOTCHG	Total charges, cleaned	Dollars	Ratio

Source: From “NIS of Data Elements. Healthcare Cost and Utilization Project (HCUP),” by Agency for Healthcare Research and Quality, 2018 (https://hcup-us.ahrq.gov/db/nation/nis/nisdde.jsp)

According to Saunders, Lewis, and Thornhill (2015), sample size is important as it increases validity and reliability of the study. Sample size such as one facility may not show the full impact within healthcare community. Small sample size may lead to lack of analytic generalization of the findings. Although multiple case study is preferred, it may lead to more expensive time-consuming outcomes. Yin (2018) advises to utilize single case study as an opportunity to shed empirical light on the concepts and principles that can be further explored and researched.

I will use a non-probabilistic convenience sampling. The convenience sampling method is appropriate when participants are selected by availability and convenience (Martínez-Mesa et al., 2016). A disadvantage to convenience sampling is that the sample is not representative of the population (Etikan, Musa, & Alkassim, 2016). I will address potential outliers and violations of the using bootstrapping within SPSS software. Software packages like SPSS have routines such as bootstrapping to address the assumptions. Kaufmann & Wittmann (2016) conducted research that demonstrated bootstrapping techniques are equivalent or better to human judges. Since the secondary data is large, I will be able to complete re-sampling as needed while meeting appropriate sample size while removing outliers and re-examining the data.

When analyzing data, descriptive statistics allow to describe data using central tendency and spread measures. I will describe the central position using mode, median, and mean (Green & Salkind, 2017). Measures of spread show how spread the variables are using the range, quartiles, absolute deviation, variance, and standard deviation (Green & Salkind, 2017). I will use tables, charts, histograms, and graphs showing the results visually and will present statistical commentary to discuss the results. Inferential statistics will allow me to generalize the population from which I will draw a sample.

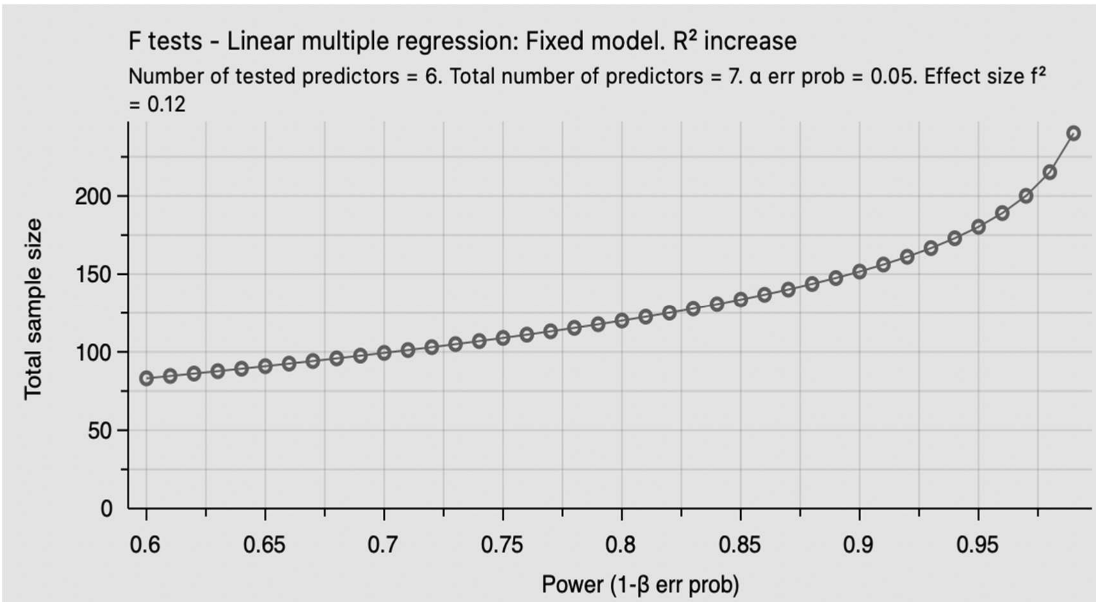
Population and Sampling

Sampling naturally incurs sampling error, and thus, inferential tests require users like me to make educated guesses to run the inferential tests (Green & Salkind, 2017). I will conduct a standard multiple linear regression, mitigate sampling error by completing power analysis and determine the minimum appropriate size. I will interpret inferential results and make conclusions based on the analyzed data.

I completed a power analysis using the G*Power version 3.1.9.6 to conduct a power analysis and determine the minimum appropriate size for this study to be 150 hospitals. A priory analysis using effect size of $f = .12$ and $\alpha = .05$ a minimum sample size of 134 hospitals to achieve a power of .85. The availability of larger sample size will allow increasing the strength and power of variable relationships. For example, examining 241 hospitals will increase the power to 0.99; thus, this study's sample size will be between 134 and 241, as presented in Figure 4.

Figure 4

G Power as a Function of Sample Size*



Source: Author's calculations

Ethical Research

The ethical requirements for the study will be covered in this session. I will analyze secondary data involving no personal identification, no human participants, and no ethical concerns related to data collection. To access HCUP data, I completed and signed the HCUP Data Use Agreement Training Course (see Appendix 1). The online course covered the importance of data protection, risk reduction of inadvertent violations, and individual responsibility when using HCUP data. I will comply with HIPAA guidelines for privacy and confidentiality of the patients and institutions. I will receive the data with encrypted coding to protect identity (AHRQ, 2020).

The Walden University requires an IRB approval (#03-18-22-0982767) to protect beneficiaries in the secondary data. I will request permission to conduct the research.

Upon approval, I will obtain the data and secure it via complex passwords on external media. Upon completion of my work, I will destroy the information suing CyberScrub after five years. I will follow all IRB protocols to ensure no violations of ethical research standards or IRB regulations.

Data Collection Instruments

I will use secondary data set in the research study obtained from the Agency for Healthcare Research and Quality archival data. I will extract data from the 2017 HCUP-NIS file. The HCUP-NIS database is federally sponsored and designed as a stratified 20 percent sample of all community hospitals' discharges. As the largest publicly available all-payer inpatient care database in the United States, the NIS database represents diverse geographical regions and hospital types (Houchens et al., 2014). Using secondary data will reduce the hardship of collecting the data and avoid expenses related to data collection.

I will use SPSS Version 28.0 for Mac to analyze data statistically and graphically (Green & Salkind, 2017). The software provides Pearson's correlation coefficient analysis, multiple regression, and descriptive statistics. SPSS is effective in analyzing large data set that predict linear relationship between multiple independent and dependent variables. I will use SPSS to examine relationships between LOS, hospital characteristics and cost of care. A null hypothesis will be accepted or rejected because of inferences made regarding relationship between variables.

Data Analysis

Researchers use several data analysis techniques to examine the relationship between variables, including t-test, ANOVA, and multiple regression. The t-test helps evaluate a hypothesis involving a single mean or the difference between two means (Green & Salkind, 2017). Quantitative DBA Doctoral studies require at least two independent variables where a t-test will not be appropriate. An analysis of variances (ANOVA) is utilized when researchers compare the averages in the groups and between the groups or from various occasions (Andres, 2017). Saunders et al. (2016) used the ANOVA model to predict continuous outcomes based on categorical predictor variables (Saunders et al. 2016). Both ANOVA and multiple linear regression are flexible, easy to use, and mighty in evaluating the relationship between independent and dependent variables (Acikkar & Sirvrikaya, 2018). However, ANOVA will not be appropriate in my work because the variables are not all categorical, and I do not plan to search for a difference between the variables on the cost of care.

In my work, I will conduct multiple linear regression. Researchers use multiple linear regression to examine the relationship between a set of predictor variables and numerical dependent variables (Saunders et al., 2016). China et al., Sarvepalli et al., and Cummins et al. examined HCUP data and recommended continuing further evaluations using multiple regression analysis due to complexity and timing. I will conduct similar work with additional variables, different set due to timing and potential changes within HCUP dataset.

l started my work by reviewing the data points for each variable to ensure there is no missing cases that I need to remove. I will review hospital characteristics such as bed size, location/teaching, region of hospital, control/ownership. I completed case processing via SPSS to find missing values. I continued by looking at extreme values for each variable and remove the data points prior further steps. Removing rows with extreme values may assist with even data distribution (Martinez-Mesa et al., 2016).

I ensured the data has even representation from each group by looking at frequency table. Because of high N value, I was able to balance the representation and still meet the requirement of the sample size. I calculated Z scores and then addressed responses with the values less than -3.5 or greater than +3.5 by removing them.

Assumptions of Multiple Linear Regression

Assumptions associated with multiple regression analysis include sample size, normality, linearity, homoscedasticity, independence of errors, and multicollinearity. Any violation may highly skew results. I will use SPSS descriptive statistics to test for assumptions. Green & Salkind (2017) and complete recommended steps to address concerns related to assumption. I examined each of these tests and presented the findings in the following paragraphs.

Sample Size. I review the variables to ensure appropriate representation of the data. It is recommended to have at least 20 data points for each variable. Based on G*Power calculation, I will ensure the sample size is meeting the requirements for my study. Strong sample size will help me to eliminate normality assumption even if I meet it.

Normality. I used SPSS to detect normality by completing normality test. I used the descriptive statistics test to examine both values for all variables. recommended that I complete a visual inspection of data plots, skewness, kurtosis, and Kolmogorov-Smirnov tests for normality. If assumption met, I would remove the outliers and will re-test to ensure the normality assumption. I will take into consideration the sample size. With the strong sample size over two hundred, the normality assumption can be overlooked, or researchers can further transform the data if the sample size is small. In my case I do not anticipate any challenges with this assumption due to a strong sample size (Green & Salkind, 2017).

Linearity. The assumption of linearity may underestimate the relationship present (Green & Salkind, 2017). The linear relationship shows deviation change in any independent variables results in the exact change to the dependent variable. I will test for linearity with scatterplots between variables. If the scatterplots will show a nonlinear association, then the assumption has been violated. In the situation like that I will review the cause of the violation and will remove the data item from the data set prior taking further steps. If the researchers are not able to remove data points due to small sample size, they may consider abandon the regression model (Green & Salkind, 2017). I do not anticipate any challenges with this assumption due to strong sample size.

Homoscedasticity. Homoscedasticity describes an equal constant variable and may be seen by the cone or bowtie shape (Green & Salkind, 2017). Violating homoscedasticity will result in bias, standard errors, and improper inferences. I will evaluate homoscedasticity in scatterplot and by looking at correlations. If the test results in heteroscedasticity, I will review each variable to ensure normal distribution and will remove the outliers. If this assumption is violated after my attempts to transform the data, I will use weighted least squares regression to address the concern. A logarithmic transformation can be applied to highly skewed variables, while count variables can be transformed using a square root transformation (Green & Salkind, 2017). According to Dr. Bradley lecture, the violation of the homoscedasticity assumption must be quite severe to present a major problem.

Independence of residual. Independence of errors checks for the assumption that there is no residual pattern, which shows that all variables stand alone, and no serial correlations are in operation (Green & Salkind, 2017). I will examine residual statistics looking for potential outliers when the Std. Residual number above values less than -3.5 or greater than +3.5. In this case, I will look at the Z scores and remove the potential outliers. I will re-analyze the data to confirm that violation is addressed. In addition, I will check Cook numbers to address anything over one as an outlier.

Multicollinearity. Multicollinearity shows independent variable dependency from other independent variables (Green & Salkind, 2017). To check for multicollinearity of the data, I used correlation matrix with SPSS to detect the possibility of multicollinearity. A variance inflation factor scores above ten indicates high variance inflation, meaning that variant is redundant with other variables (Green & Salkind, 2017). If the data meets multicollinearity assumption, I may consider removing one of the predictive variables or use rig regression. The coefficient output in collinearity statistics the VIF value below ten will indicates that multicollinearity is not a concern.

Linear regression assumptions ensure that the variable data is trustworthy, accurate, and reliable. After completing descriptive statistics, I will mitigate assumptions by removing the outliers obtaining extensive sample data to complete my work. I will look for outliers, normality, linearity, homoscedasticity, and independence of residuals by examining the Normal Probability Plot (P-P) of the regression standardized residuals and the scatterplot of the standardized residuals. The examination will indicate no significant violations of the assumption when the tendency of the points lies in a reasonably straight line, diagonal from the bottom left to the top right will provide supportive evidence that the assumptions of normality will not be grossly violated (Green & Salkind, 2017). The lack of a transparent or systematic pattern in the scatterplot of the standardized residual will support the tenability of the assumptions being met (Green & Salkind, 2017). In addition, I will use a bootstrapping technique to mitigate the possible implications of any data assumptions and a 95% confidence interval based upon the bootstrapping samples.

According to Green & Salkind (2017), scholars frequently rely on beta weights and their confidence intervals when interpreting inferential results. I will review inferential results by examining beta weights, confidence intervals, significance values, R^2, and F values. P-values and coefficients in regression analysis will tell me which relationships are statistically significant and the nature of those relationships (Greenland et al., 2016). The coefficients describe the mathematical relationship between independent and dependent variables (Greenland et al., 2016). Beta weight determines an independent variable's contribution to the regression effect while all other independent variables remain constant (Green & Salkind, 2017). Confidence interval predicts the range of values of the true population based on the probability of 95% containing the true value (Greenland et al., 2016). R^2 is the numerical measure of the variance in the dependent variable attributed to the predictor variables, and it can range from 0 to 1 (Green & Salkind (2017). These and more inferential results I will review in more detail in section three of the study

Study Validity

Validity is defined as a measurement of the study where the findings can be generalized, operationalized, and transferable (Yin, 2018). Both definitions of reliability and validity are important in creating successful research but have distinct characteristics. Validation of the studies plays a vital role where findings may lead to the next one or cancelation of the survey altogether. In some medical cases, education may pursue a step further taking the research to clinical trials (Araya, Gebretekle, Gebremariam, & Fenta, 2019). Because participants may not always agree with each other or with a researcher, validity creates moments of conflict and challenge with epistemic authority (Caretta, & Pérez, 2019).

Validity refers to the facts that a tool measures exactly what is proposes to measure (Green, & Salkind, 2017). It is not an instrument characteristic, and it must be determined regarding specific situation. Reliability and validity should always be tested (Chaudhary, Rangnekar, S., & Barua, 2013). They are not totally independent. Souza et al. (2017) confirmed that instruments that are not reliable cannot be valid, but reliable instruments can be invalid. Thus, high reliability does not ensure validity. For the conclusion to be valid the independent variables must be the only factors that influences the dependent variable. There are many other confounding variables that can influence profitability of the hospitals.

Transition and Summary

The purpose of this quantitative correlational study will be to examine the relationship between inpatient hospital (a) LOS, (b) hospital characteristics, and (c) cost of care. The sample will be obtained from HCUP data set which publicly available for download. Descriptive analyses will describe the study population and provide the means, standard deviations, frequencies, a range of scores, and percentages (Creswell & Creswell, 2018). The data analysis will promote opportunity further compare specific healthcare characteristics to determine whether health care cost vary depending on the type of the hospital used by customers. The results of the data analysis will be presented in section three.

Section 3: Application to Professional Practice and Implications for Change

Executive Summary

In 2018, U.S. healthcare spending reached 3.6 trillion dollars, equivalent to 17.7% of GDP (Cai et al., 2020). It was vital for us to understand how to mitigate the challenges associated with the rising healthcare cost. A good understanding of variables impacting the cost of inpatient hospital stay will enable the healthcare community and its leaders to respond to society's needs more effectively. In this section, I represent the summary of the research findings and the potential implications for social change.

Purpose of the Study

The purpose of this quantitative ex post facto correlational study was to examine the relationship between inpatient hospital (a) LOS, (b) hospital characteristics, and (c) cost of care. The independent variables are the LOS and hospital characteristics. The dependent variable is the cost of care. The target population will consist of community hospitals participating in the Nationwide Inpatient Sample (NIS) data collection. The geographical location will be the United States. Hospital administrators, healthcare stakeholders, and patients might use the study's findings to choose facilities, negotiate prices, and make better business decisions. The implications for positive social change include a better understanding of the correlation of care cost, thus shining a light on additional strategies to make healthcare more affordable and accessible to a larger population.

This secondary data analysis aimed to review if a relationship exists between hospital characteristics, length of stay, and cost of care. Understanding if a relationship exists and its impact may be valuable in selecting an inpatient hospital for a more cost-effective inpatient hospital stay. Mitigating the rise of healthcare costs could positively contribute to society and better access to healthcare. My objective for this study was to review another angle of healthcare cost for the healthcare community to consider.

Presentation of the Findings

Using 2017 NIS HCUP data from AHRQ, I reviewed the following hospital characteristics: hospital bed size, hospital location/teaching status, region of hospital, and control/ownership. The following subsections answer the research question and exhibit the finding from the study. I present finding using descriptive statistics followed by statistical results from the data analysis. I used the multiple linear regression analysis functions in SPSS statistical software to examine the relationship between the independent and the dependent variables. A significant regression equation found F (4, 299) = 10.60, p=.00, R^2=.15. The null hypothesis was rejected because the significance (p) was less than .05.

Descriptive Statistics

The data included bed size of the hospital, location/teaching status of the hospital, control ownership of the hospital, region of hospital, length of stay, and total charges. Table 2 depict descriptive statistics for the study variables (mean, 15059.9; standard deviation, 9404.6). I visually scanned the data to discard incomplete or missing data elements after meeting the sample size calculated with the G*Power (see figure 4). The data included sample size information from 300 hospitals for all of 2017. The purpose of screening data was to check all assumptions of the multiple linear regression model to have any residual plots, histograms, and normal P-P plots.

Table 2

Descriptive Statistics

	Mean	Std. Deviation
Total Charges	15059.8	9404.6
Bed size of hospital	1.6	0.8
Location/teaching status of hospital	1.8	0.8
Control/ownership of hospital	2.0	0.8
Region of hospital	2.6	1.0
Length of stay	3.1	2.1

Note: Source: SPSS Output, N=300

Testing of Assumptions

I used several tests of assumptions to guide me in validating the findings of the research study. These tests included multicollinearity, normality, linearity, homoscedasticity, outliers, and independence of residuals. I examined these tests and presented the findings in the following paragraphs.

Multicollinearity is represented by the variance inflation factor (VIF). VIF values of five or greater indicate the presence of multicollinearity (Levine et al., 2017). Based on the coefficient output, collinearity statistics, an obtained VIF value indicates that multicollinearity was not a concern (see Table 3)

Table 3

Collinearity Statistics

Variable	Tolerance	VIF
Bed Size of hospital	.932	1.073
Location/teaching status	.887	1.127
Control/ownership of hospital	.945	1.058
Region of hospital	.970	1.031
Length of stay	.991	1.009

Note: Dependent variable =Total Charges; *N*=300

Linearity was evaluated through the residual scatterplot to assess if the points were randomly distributed around the mean value of zero. Figure 5 illustrates the scatterplot. Visually examining the scatter plot, I found that results distributed unevenly. A set of results are skewed to the left. Therefore, this distribution of data indicated that linearity was a concern, and the linearity assumption was violated. I used bootstrapping technique to combat the possible implications of any data assumption violations. Based on a one thousand bootstrap sample and 95% confidence interval, there were not a statistically significant correlation between variables.

I used a Durbin-Watson test with SPSS to detect the possibility of homoscedasticity. Table 4 shows a statistical value of less than 1.5, indicating a violation of the assumption.

Figure 5

Residual scatterplot for linearity and homoscedasticity

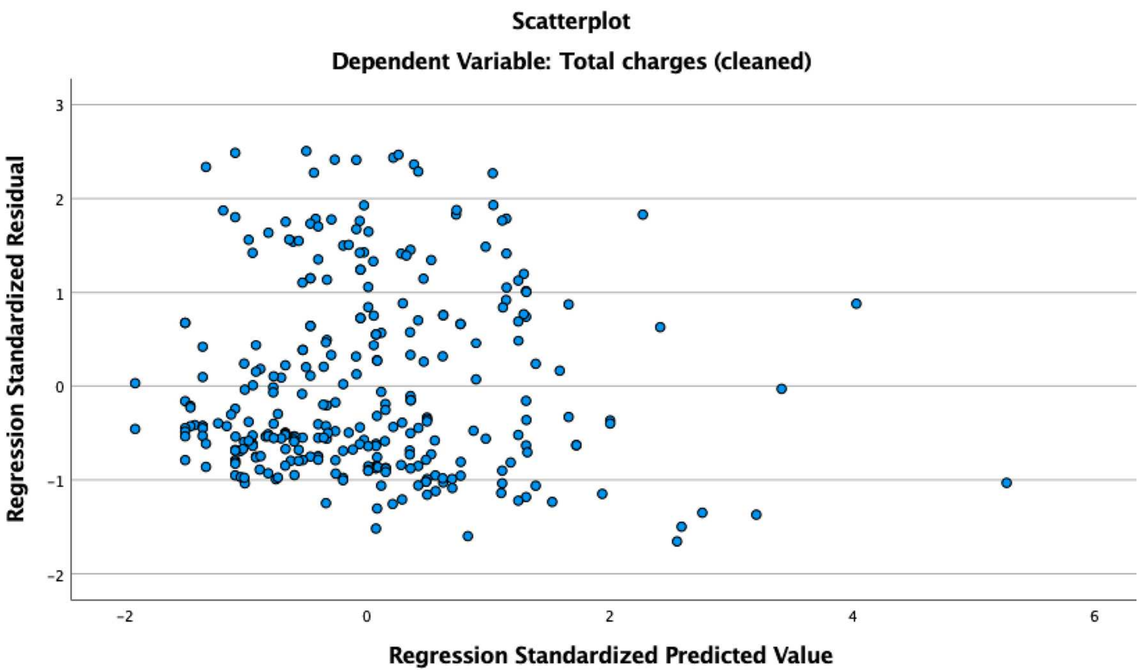


Table 4

Durbin-Watson Test Summary[b]

Model	R	R^2	Std. Error of the Estimate	Durbin-Watson
1	.39[a]	.15	8730.2	.01

Note: *N*=300
a. Predictors: LOS, Control/ownership of hospital, Region of hospital, Bed size of hospital, Location/teaching status of hospital.
b. Dependent variable: Total charges

Independence of residual included normality violation by examining the normal probability plot (P-P). Figure 6 illustrates abnormal probability plot (P-P) of the regression standardized residual. The data points follow a reasonably straight line, diagonal from the bottom left to the top right. However, the data points were not clustered near the plotline, providing evidence that the assumption of normality was violated (Levine et al., 2017). Histogram suggested that residuals are not normally distributed (see Figure 7). The results shows that not all variables stand alone, and there are serial correlations are present (Green & Salkind, 2017). I dismissed independence of residual violation because Cook numbers remained in check (see Table 6).

Figure 6

Normal P-P of regression standardized residual

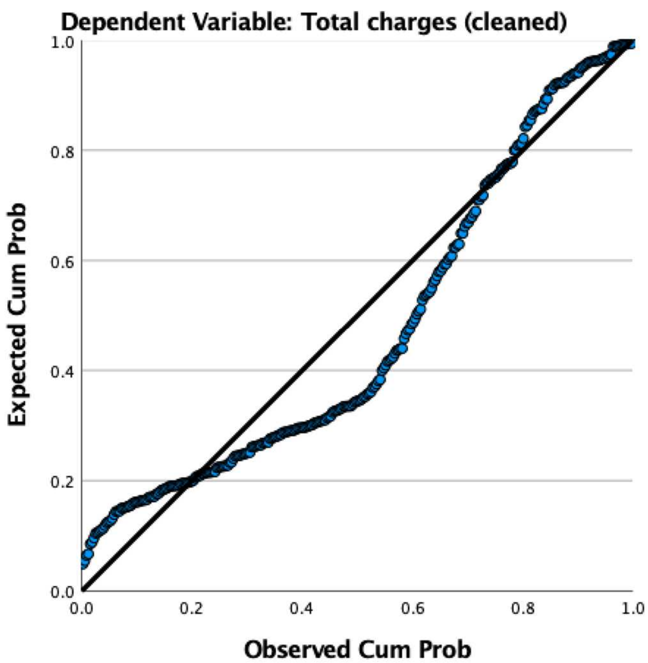
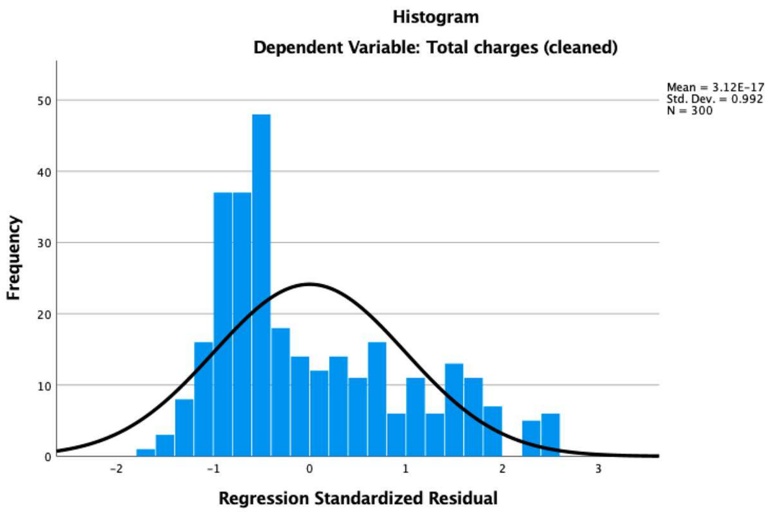


Figure 7

Histogram



A test of normality confirmed the suspicion. Table 5 showed statistically significant Sig.< 0.05. However, it means that the test for normality is violated since the sample size is 300. It is a strong sample size where the normality assumption can be dismissed. Standard residual statistics did not show any outliers. Z score varied from -1.654 to 2.506, indicating acceptable data set (see Table 6).

Table 5

Test of Normality

Variable	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig
Bed Size of hospital	.35	300	<.001	.72	300	<.001
Location/teaching status	.29	300	<.001	.77	300	<.001
Control/ownership of hospital	.22	300	<.001	.80	300	<.001
Region of hospital	.26	300	<.001	.86	300	<.001
Length of stay	.21	300	<.001	.83	300	<.001
Total charges	.15	300	<.001	.91	300	<.001

Note: a. Lilliefors Significance Correction; N=300

Table 6

Residual Statistics

	Minimum	Maximum	Mean	Std. Deviation
Predicted Value	8017.22	34430.78	15059.76	3674.84
Std. Predicted Value	-1.92	5.27	.00	1.00
Std. Error of Predicted value	699.95	3205.31	1205.34	267.80
Residual	-14439.92	21878.03	.00	.86
Std. Residual	-1.70	2.51	.00	.83
Mahal. Distance	.93	39.31	4.98	.91
Cook's Distance	.00	.03	.00	.01
Centered Leverage Value	.00	.13	.02	.01

Note: a. Dependent Variable: Total Charges. *N=300*

Inferential Statistics

I conducted a standard multiple regression, α=.01 (two-tailed), using secondary data to examine the relationship between hospital characteristics, length of stay, and total charges in healthcare within the U.S. The dependent variable was total charges that represented inpatient care costs. The null hypothesis was that there is no statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care. The alternative hypothesis was that there is a statistically significant relationship between inpatient hospital length of visit, hospital characteristics, and cost of care. The β (standardized coefficients) represent how much the cost of care will increase or decrease. The multiple linear regression model could significantly identify gross charges growth: F (4, 299)=10.60, p=.00, R^2=.15. The R^2 (.15) value indicated that approximately 15% of variations in total charges are accounted for by the linear combination of the independent variables. In the final model (Total Charges Ratio= 9678.78+629.90(bed size)+ -993.53(location/teaching)+1752.14(control/ownership)+ -762.52(region)+1516.41(LOS)) length of stay was statistically significant predictor (t=6.22, p=.00, β=.34) and control/ownership of hospital was statistically significant predictor (t=2.76, p=.01, β=.15), accounting for a higher contribution to the model than any of the hospital characteristics (Green and Salkind, 2017). Table 7 depicts the regression summary. The results of the multiple linear regression were significant, F(4, 299) = 10.60, $p < .001$, $R^2 = .15$. In the final model, only two of the predictors were significant, length of stay (t = 6.22, p = .00, β = .34) and control/ownership of hospital (t = 2.78, p = .01, β = .15).

Table 7

Regression Analysis Summary for Independent Variable

Variables	*B*	*SE B*	*β*	*t*	p
Bed Size of hospital	629.90	669.67	.052	.94	.35
Location/teaching status	-993.53	657.41	-.09	-1.51	.13
Control/ownership of hospital	1752.14	642.98	.15	2.76	.01
Region of hospital	-762.52	508.92	-.08	-1.50	.14
Length of stay	1516.41	243.86	.34	6.22	.00

Note. *B*=unstandardized coefficient; β=standardized coefficient; *t*=coefficient divided by standard deviation; *p*=significance; *N*=300. Dependent variable =Total Charges

Many violations were identified, however based on a bootstrapping estimation technique there was not a statistically significant correlation between independent variables. Table 8 includes the correlation summary of the variables. A correlation analysis is used to identify an initial relationship between variables (Field, 2018).

Table 8

Pearson Correlation

	Total Charges	Bed size of hospital	Location/teaching status of hospital	Control/ownership of hospital	Region of hospital	Length of stay
Total Charges	1.00	.08	-.04	.14	-.10	.35
Bed size of hospital	.08	1.00	.23	.07	-.13	.07
Location/teaching status	-.04	.23	1.00	.23	-.14	-.02
Control/ownership of hospital	.14	.07	.23	1.00	-.04	.01
Region of hospital	-.10	-.13	-.14	-.04	1.00	-.05
Length of stay	.38	.08	-.02	.01	-.05	1.00

Note: N=300

I selected the quantitative correlation research design to examine the relationship between inpatient length of stay, hospital characteristics, and cost of care. A standard multiple linear regression, α=.05 (two-tailed), was used to examine the relationships among independent and dependent variables. The independent variables were hospital characteristics, including bed size, location, region, ownership of the hospitals, and the average length of stay. The dependent variable was the cost of care. The null hypothesis and alternative hypothesis were:

Null hypothesis (H0): There is no statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

The alternative hypothesis (H1): There is a statistically significant relationship between inpatient hospital length of stay, hospital characteristics, and cost of care.

The study results showed that the null hypothesis was rejected because a statistically significant relationship with control/ownership of hospital, length of stay, and cost of care exists. The alternative hypothesis was accepted. For overall regression model was significant, with both variables showing the need to further explore predictive modeling for the cost of care.

Recommendations for Action

This quantitative ex post facto correlational study aimed to examine the relationship between inpatient hospital LOS, hospital characteristics, and cost of care. This research study showed a strong/weak relationship between variables and should be further investigated to include demographic served. This study suggested the need to pay attention to the hospital characteristics despite the length of stay and cost of care. Hospitals may use resources differently based on many factors including size, teaching status, ownership, internal priorities, and leadership styles. System analysis that shows predictive modeling should be the next step for future research.

This study is subject to some limitations. First, it excludes healthcare outside the United States. I did not cover outpatient stings and services, including other care delivered outside hospitals, which play vital roles in the comprehensive care delivery model. Second, time was limited to 2017, and it would be beneficial to look at a multi-year study to eliminate assumptions based on one year alone. Researchers may wish to investigate statewide reporting datasets or global views considering vast advancements in telehealth in the sight of recent changes. Finally, the outcomes are limited to multiple regression analysis. Different modeling approaches may improve the statistical accuracy of metrics with adjustments for reliability, which the scope of one study limited.

Communication Plan

Knowledge sharing is an essential element of growth and improvement. Lee Iacocca once said, "You can have brilliant ideas, but your ideas won't get you anywhere if you cannot get them across." The Healthcare cost subject is too important not to share the research findings I completed. I will communicate the knowledge gained through media, research publications, presentations at conferences and department meetings, and potential consulting opportunities.

I will use several channels to communicate my research findings. First, I will submit the completed DBA SEC to ProQuest, a Walden University requirement for graduation. Second, as a Fellow of the American College of Healthcare Executives, I plan to publish in Healthcare Executive journal and the American Nurses Association journal.

Last, I plan to obtain a fellow status in the Healthcare Financial Management Association, where I can present my knowledge and further advance sharing my research findings.

Implications for Social Change

This quantitative correlational study examines the relationship between inpatient length of stay, hospital characteristics, and cost of care. The finding of this study may contribute to the public through the potential to better understand what impacts growing healthcare costs. The ability of the people to make better decisions while choosing a hospital to be a provider of choice may lead to a better economic standing of the overall community while driving healthcare costs down. The ability of public and healthcare leaders to recognize the relationship between hospital characteristics, length of stay and cost of care will bring sustainable economic improvement. Furthermore, the value provided to communities and society involves lower prices, allowing healthcare to become more affordable, expanding the reach beyond current potential (e.g., public health, education, reach of services, and the environment).

A person should not choose to afford the food or get healthy based on income. Healthcare facilities should be accountable for providing optimal value-based care. Learning more about factors associated with rising healthcare costs will guide healthcare leaders to make better decisions and add value externally to the population.

Skills and Competencies

The DBA program was an exciting and challenging journey. I have acquired skills and competencies throughout the journey that will make me a better business leader, researcher, and practitioner. My professional experience as a hospital administrator, nurse leader, and financial decision-maker, made me more successful in writing the dissertation and questioning theoretical and practical implications. I became better at time management, prioritizing tasks, and critical reading of the presented knowledge. Through the literature review process, I learned to question existing published findings, look for topic-specific databases and present my result in a way others can understand. Secondary data analysis gave me insight into statistics and large data set management and analysis. This experience introduced me to evaluation and predictions, teaching me more about examining relationships and further understanding of healthcare cost analysis.

My DBA portfolio, including my skills, certification, and competencies as a business leader can be accessed through https://waldenu.optimalresume.com/modules/documentcenter.php.

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Appendix A: HCUP Data Use Agreement Training

CERTIFICATE OF COMPLETION

Awarded To

Maria Mikhataykina

For Successfully Completing

HCUP DATA USE AGREEMENT TRAINING

On

09/05/2020

YOUR CERTIFICATION CODE IS:

HCUP-74IWR48L3

DEPARTMENT OF HEALTH & HUMAN SERVICES • USA

AHRQ

Agency for Healthcare Research and Quality

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H·CUP

HEALTHCARE COST AND UTILIZATION PROJECT

Appendix B: CITI Program Certificate

CITI PROGRAM

Completion Date 07-Feb-2022
Expiration Date 06-Feb-2025
Record ID 44260601

This is to certify that:

Maria Mikhataykina

Has completed the following CITI Program course:

Not valid for renewal of certification through CME.

Clinical Research Coordinator (CRC)
(Curriculum Group)
Clinical Research Coordinator (CRC)
(Course Learner Group)
1 - Basic Course
(Stage)

Under requirements set by:

University of Texas Health Science Center at Houston

CITI
Collaborative Institutional Training Initiative

Verify at www.citiprogram.org/verify/?wf55a1cd2-1493-4c9d-9c74-cdae4f2f1657-44260601

Appendix C: Example of Dataset Details

AHRQ Agency for Healthcare Research and Quality

Search All AHRQ Sites | Careers | Contact Us | Español | FAQs | Email Updates

H·CUP

NIS Overview
The National (Nationwide) Inpatient Sample (NIS) is a set of longitudinal hospital inpatient databases included in the HCUP family. These databases are created by AHRQ through a Federal-State-Industry partnership.

Search HCUP-US

HCUP Home | Databases | Research Tools | Reports | Data Visualizations | Data Query Tools | News & Events | Purchase HCUP Data | Technical Assistance

Overview of the National (Nationwide) Inpatient Sample (NIS)

The National (Nationwide) Inpatient Sample (NIS) is part of a family of databases and software tools developed for the Healthcare Cost and Utilization Project (HCUP). The NIS is the largest publicly available all-payer inpatient healthcare database designed to produce U.S. regional and national estimates of inpatient utilization, access, cost, quality, and outcomes. Unweighted, it contains data from more than 7 million hospital stays each year. Weighted, it estimates more than 35 million hospitalizations nationally. Developed through a Federal-State-Industry partnership sponsored by the Agency for Healthcare Research and Quality (AHRQ), HCUP data inform decision making at the national, State, and community levels.

BEGINNING WITH DATA YEAR 2016, THE NIS CONTAINS A FULL YEAR OF ICD-10-CM/PCS CODES.

Beginning with data year 2016, the NIS includes a full calendar year of data with diagnosis and procedure codes reported using the ICD-10-CM/PCS[1] coding system. The file structure is similar to the file structure of the NIS in data years 2014 and prior years.

THE 2015 NIS CONTAINS ICD-9-CM AND ICD-10-CM/PCS CODES.

On October 1, 2015, hospital administrative data began using ICD-10-CM/PCS, so the first nine months of 2015 contain ICD-9-CM codes and the last three months contain ICD-10-CM/PCS codes. The data elements and file structure for the 2015 NIS are different. Trends based on diagnoses or procedures will be affected.

AHRQ SOFTWARE TOOLS FOR ICD-10-CM/PCS CODES

- Data elements derived from AHRQ software tools are not available for ICD-10-CM/PCS data on the 2016-2017 NIS.
- Beginning with data year 2018, data elements derived from the Clinical Classifications Software Refined (CCSR) for ICD-10-CM diagnoses are available in the NIS.
- Beginning with data year 2019, data elements derived from the Elixhauser Comorbidity Software Refined for ICD-10-CM, the CCSR for ICD-10-PCS procedures, and Procedure Classes Refined for ICD-10-CM are also available in the NIS.

THE NIS WAS REDESIGNED BEGINNING WITH 2012

Starting in data year 2012, the NIS is a **sample of discharges** from all hospitals participating in HCUP. For prior years, the NIS was a **sample of hospitals**. For details, see the *2012 NIS Redesign Report*.

[1] ICD-9-CM: International Classification of Diseases, Ninth Revision, Clinical Modification; ICD-10-CM/PCS: International Classification of Diseases, Tenth Revision, Clinical Modification/Procedure Coding System

This page provides an overview of the NIS. For more details, see NIS Database Documentation and the *Introduction to the NIS, 2019* (PDF file, 1.1 MB; HTML).

Contents: