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Medicare Expansion and Access to Quality Care in a Rural Long-Term Care Hospital in Tennessee

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Abstract

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

The research problem addressed in this study is that it was not known whether differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. The purpose of this quantitative descriptive study was to determine whether such differences exist. The conceptual framework that guided this study is the Donabedian framework. The research question was addressed that focused on the difference in the rate of potentially preventable hospital readmissions 30 days after discharge and on the difference in the potentially preventable 30-day readmission rates compared to the national preventable 30-day readmission rates. Data were obtained from 202 patients in urban and rural long-term care hospitals in Tennessee whose readmission data have been documented in the Centers for Medicare and Medicaid Services database. The difference in the 30-day readmission rates between the urban hospital and rural hospital was assessed using independent sample *t* test, and multiple linear regression was used to assess whether being elderly from rural long-term care hospitals predict the likelihood of being readmitted 30 days after discharge. The outcome showed that there is higher number of eligible stays and potentially preventable readmissions in the rural long-term care hospitals compared to the urban long-term care hospitals. Implications for positive social change include the need for interventions that could improve quality care among older adults specifically in Tennessee's rural areas to reduce the number potentially preventable readmissions.

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Dedication

This dissertation is dedicated to all those who believed in me and made this journey possible. To my family, your love, sacrifices, and encouragement enabled me to take and complete this journey. You believed in my capabilities and had unwavering faith in me, which inspired me to overcome every obstacle.

To my mentors and advisors, your guidance and expertise propelled me to seek knowledge and pursue excellence. Through your wise counsel, constructive criticism, and mentorship I sought to exceed my expectations and achieve new intellectual heights. To my friends and peers, who shared this academic journey with me. Your friendship, support, insights, and collaboration made the research process smoother and enriching. You helped me navigated the complexities of academia.

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Section 1: Foundation of the Study and Literature Review

Introduction

This study examines 30-day readmission rates among the elderly in urban and rural long-term hospitals. The elderly population in developed countries such as the United States is increasing at rapidly rate and it is expected that by 2030 about 25% of the U.S. population will be aged >85 years (Ko et al., 2019). Older individuals are at an increased risk for diseases including comorbidities (Dai et al., 2021; Esme et al., 2019). Additionally, the increasing aging population is expected to put pressure on available funding. This could lead to compromise on available health and social care services, increasing the risk of hospital readmissions (Spiers et al., 2019). Garcia et al. (2019) noted that the mortality rates due to chronic diseases is significantly high among the rural communities, which make up about 19% of the U.S. population. Researchers have also indicated that the rural elderly experience poor health and increased risk of death compared to urban elderly which could be attributed to the barriers to healthcare access (Garcia et al., 2019; Schreckinger et al., 2021). Elders living in rural communities may be faced with the challenge of accessing healthcare due to spatial distance, social isolation, low economic status, limited healthcare providers, particularly the medical specialists (Fulmer et al., 2021).

This study focused on access to quality care in a rural long-term care. This is important because older adults comprise the highest proportion of the Americans living in the rural communities (Jensen et al., 2020; Shebehe & Hansson, 2018). The 30-day readmission rate is considered an indicator of quality care and impacts the cost of care

(Meurs et al., 2021; Rubin et al., 2017; Wish, 2014). However, evidence is limited and at best contradictory regarding the difference, if any, in the 30-day readmission rates among the elders living in urban versus rural long-term hospitals (Bennett et al., 2019; Clement et al., 2018; Kosar et al., 2020). The potential positive social change implications associated with the study is fostering of successful ageing. It is hopeful that the findings of the study will equip the relevant stakeholders with up-to-date information regarding 30-day readmissions in urban and rural long-term hospitals, which can enable them to put in place strategies to minimize the readmissions and the associated costs and health concerns. The long-term goal of reducing hospital readmissions will eventually enhance quality of life among the aging while also reducing burden to healthcare facilities.

In this section, I provide the background information consisting of a summary of relevant literature that helps to anchor the study topic within the existing literature. I also discuss the problem statement by identifying the issue of 30-day hospital readmission in urban and rural long-term hospitals among the elderly. The purpose of the study which is to determine the differences between 30-day hospital readmissions rates between urban and rural hospitals among the elderly. The research question, hypotheses and Donabedian as a theoretical framework that guides the study. I also provide a brief description of the nature of the study and an in-depth assessment of literature for the variables in research question. Finally, I define the key terms and present assumptions, the scope of the study, limitations, and significance.

Background

The population of Americans aged above 65 years is expected to increase from 47.8 million in 2015 to about 87.9 million in 2050, which is an increase of about 84% (Harris-Kojetin et al., 2019). Fulmer et al. (2021) also noted that people aged 65 years and over will exceed the younger population (64 years and under) in the United States by 2030. Given the anticipated increase in the population of the elderly, Fulmer et al. (2021) noted the need for the government to put in place strategies to address potential increase in need for care and align the public health services with the needs of the elderly.

The U.S. Department or Health and Human Services promotes long-term care facilities in dealing with the various chronic health challenges among the elderly (Harris-Kojetin et al., 2019). The 2010 Patient Protection and Affordable Care Act (ACA, P.L. 111-148, as amended) refers to long-term care facilities as long-term services and support targeting health care- related and non-health care-related services (Harris-Kojetin et al., 2019). As noted by Harris-Kojetin et al. (2019), the long-term care hospitals offer important care services needed by frail elderly people with chronic illnesses, cognitive or mental disabilities and other health-related challenges. The number of older Americans using long-term care services is expected to gradually grow in the coming years (Harris-Kojetin et al., 2019).

However, access to healthcare among the elderly in America could be impacted by whether one live in urban or rural counties (Cyr et al., 2019; Foutz et al., 2017). Rural versus urban population being made up of the elderly (Cyr et al., 2019; Foutz et al., 2017). Evidence suggests that rural and urban Americans differ based on their income levels and employment status. According to Foutz et al. (2017), high number of rural Americans have high rates of unemployment and low-income status compared to their urban counterparts. Additionally with the rural Americans have lower level of education compared to the urban population (Cyr et al., 2019). The highlighted demographic features of the urban and rural population could influence the access to health.

Concerns have been raised regarding health challenges facing people living in rural areas. According to Jensen et al. (2020), the rural United States have a large proportion of older and sicker people. Mandal (2022) indicated that the risk of chronic conditions is higher among people living in rural areas compared to their urban counterparts. According to Foutz et al. (2017), rural American populations face significant health challenges which could be associated with limited access to health and health coverage. Evidence has indicated that there are concerns regarding the rate of hospital closures in rural areas, which further put strain on access to quality health care. Germack et al. (2019) reported closure of about 100 rural hospitals in the past 10 years due to limited funding, lack of sufficient facilities, and unsustainable financial health. Germack et al. also attributed the limited health facilities in rural areas to the insurance coverage, employment status, and poverty level of the rural population. The highlighted health challenges associated with rurality could be amplified among the elderly.

Efforts by Federal government through Medicaid expansion target increased access to health care among the elderly especially in the low-income neighborhoods (Gruber & Sommers, 2019; Guth et al., 2020). The Medicaid expansion provides access to insurance coverage to low-income elderly members of the society who due to existing condition would face challenges acquiring private cover (Gruber & Sommers, 2019; Guth et al., 2020). However, with the introduction of expansion of Medicaid, the demand for healthcare has increased, putting pressure on health facilities and financial burden on the federal and state governments (Cole et al., 2017; Gruber & Sommers, 2019).

According to Holahan et al. (2017), national health expenditures are high and stand at about 18.3% of the gross domestic product, which is higher than health expenditures of other developed nations and remains a problem that needs to be fixed by the federal and the state government. Medicaid program cost was about $600 billion in 2017 (Franco Montoya et al. 2020). One of the causes of increased cost of care is hospital readmissions. Kocakulah et al. (2021) noted that the hospital readmission resulted in additional costs amounting to $26 billion in 2013. Additionally, concerns have been raised regarding the cost and access to long-term care. About 50% of elderly Americans need long-term care services averaging cost of $138,000 (Harris-Kojetin et al., 2019). The largest portion of the costs of long-term care is met by Medicaid financing (Nguyen, 2017). Concerns have also been raised regarding the lack of qualified workforce in long-term care facilities, which raises concerns over whether the elderly in such facilities receive quality care (American Health Care Association & National Center for Assisted Living, 2021).

Evidence indicates the one of factors that drive the cost up is the high readmission rates, especially the 30-day readmission (Kocakulah et al., 2021; Meurs et al., 2021; Rubin et al., 2017). The 30-day readmission measures focus exclusively on the unplanned readmissions occurring within 30 days after discharge regardless of cause or primary diagnosis (Rubin et al., 2017). Lembeck et al. (2019) noted that unplanned readmissions are costly yet preventable. High rates of hospital readmission especially within 30 days of discharge put further pressure on the available resources. For example, in 2013, 18% of Medicare patients were readmitted 30 days after discharge and was estimated that the preventable readmission resulted in additional US$26 billion (Kocakulah et al., 2021; Meurs et al., 2021). Readmission of patients within 30 days after discharge is also considered a quality indicator for hospital treatment and primary care (Wish, 2014; Rubin et al., 2017; Meurs et al., 2021). Lembeck et al. specifically pointed out that the readmission of patients within 30 days after discharge implies that the initial treatment offered to the patient and subsequent discharge was insufficient. It should be noted that readmissions are associated with increased morbidity and mortality also causes reduced patient satisfaction (Meurs et al., 2021).

Evidence suggests that some of the 30-day readmission are caused by preventable factors (Lembeck et al., 2019; Uitvlugt et al., 2021; van der Does et al., 2020). According to Lembeck et al. (2019), steps that can be taken to prevent pre-admission include primary management of the patient. Van der Does et al. (2020) observed that addressing specific features related to diagnostics, medication, and management could help to reduce up to 13% of the cases of hospital readmissions 30 days after discharge. According to Uitvlugt et al. (2021), 16% of readmissions within 30 days after hospital discharge are as result of medication related problems that can be prevented. Auerbach et al. (2016) noted that increased readmission is associated with inadequate post-discharge follow-up, lack of discussions about care goals, premature discharge and patients lacking hospital contact information. Misky et al. (2018) associated hospital readmission with therapeutic misalignment, social fragility, access failure, and the disease behavior.

The risk of readmission increases with age, putting older individuals at higher risk (Goto et al. 2017; Schreckinger et al., 2021). Glans et al. (2020) noted that elderly patients (aged 65 years and more) make up 56% of the readmissions 30 days after discharge. Goto et al. (2017) reported higher percentage (65%) of elderly patients 30-day readmission. There are various factors that could increase the risk of readmission of elderly patients 30 days after discharge that include functional status, illness severity, comorbidity, polypharmacy, diagnosis or presenting illness (Lee, 2012).

Medicare has taken steps to cut cost associated with hospital readmissions (James, 2013; Joynt & Jha, 2013; Evans et al., 2021). The Centers for Medicare and Medicaid Services' (CMS) Hospital Readmissions Reduction Program seeks to reduce readmission using imposing financial penalties for excessive readmissions (James, 2013; Joynt & Jha, 2013). Ferro et al. (2019) reported that the implementation of Hospital Readmissions Reduction Program has resulted in reduced readmission among Medicaid patients. The Community-Based Care Transitions Program developed by CMS also address hospital readmissions by helping patients to transition (Evans et al., 2021).

It should be noted that evidence is contradictory regarding the 30-day hospital readmission among the rural and urban elderly populations. Some researchers indicate that the 30-day readmission rates among the elderly in rural areas is significantly higher than in urban settings. Kosar et al. (2020) noted that among Medicare beneficiaries with chronic diseases, the 30-day readmission rates were higher in the rural counties compared to the urban counties. However, other researchers indicate that the 30-day hospital readmission rates among the elderly in urban areas is significantly higher than in rural settings. According to Clement et al. (2018), the risk-adjusted 30-day hospital readmission rates is higher in urban areas, followed by suburban areas then large rural towns, and the lowest in rural areas. Clement et al. based their study on data retrieved from the CMS Nursing Home Compare (CMS-NHC) website. Bennett et al. (2019) also noted that rate of 30-day readmission was low in the rural hospitals compared to urban hospitals. Bennett & Probst (2016) also reported that rural dually eligible beneficiaries had lower rates of 30-day readmission compared to the urban dually eligible beneficiaries. Based on the analysis of data from health insurance database. Shebehe and Hansson (2018) also noted that the 30-day hospital readmission rates is higher among the elderly living in low socioeconomic status neighborhoods such as rural setting. Ko et al. (2019) reported no statistically significant difference in the utilization among people aged 60 years and more residing in the urban and rural areas.

It is therefore evident that there is a gap regarding whether there is difference in the potentially preventable hospital readmissions 30 days after discharge between rural and urban settings. Importantly, there is limited evidence focusing on the urban and rural 30-day hospital readmission in long-term care hospitals. Addressing this gap is vital because of two reasons. The first reason is related to the need to cut down on additional cost associated with 30-day hospital readmissions. The second reason is related to the concerns regarding the quality of care associated with high rates of 30-day hospital readmissions. By examining the differences 30-day hospital readmission between rural and urban long-term care hospitals will provide insights that stakeholders could use to address the cost and quality concerns.

Problem Statement

In this study, the research problem is that it is not known if differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. The highlighted problem is current because the United States is experiencing an increase in the people aged 65 years and more and expected to exceed the younger population by 2030 (Fulmer et al. 2021). With the increasing number of the elderly comes the increasing susceptibility to chronic diseases and various comorbidities (Esme et al., 2019; Dai et al., 2021). Most of the elderly live in rural areas where concerns have been raised regarding access to care (Germack et al., 2019; Jensen et al., 2020). Federal government through Medicaid expansion has taken action to enhance access to care by providing insurance coverage to low-income elderly members of the society who due to existing condition would face challenges acquiring private cover (Gruber & Sommers, 2019; Guth et al., 2020). But with increased coverage healthcare construction is increased and put pressure on health facilities raising concerns regarding the quality of care and cost of care (Cole et al., 2017; Gruber & Sommers, 2019).

Medicaid's attempts to address the runaway costs and concerns regarding quality of care involves the use of measures based on 30-day readmission (James, 2013; Joynt & Jha, 2013; Evans et al., 2021). However, there are still questions whether interventions by CMS such as Hospital Readmissions Reduction Program and Community-Based Care Transitions Program have successfully addressed the 30-day readmissions rates (Joynt &

Jha, 2013; Evans et al., 2021). Evidence is limited and at best contradictory regarding the difference, if any, in the 30-day readmission rates among the elderly between urban and rural long-term hospitals (Bennett et al., 2019; Clement et al., 2018; Kosar et al., 2020). According to Kosar et al. (2020), the 30-day readmission rates are higher among Medicare beneficiaries in the rural counties compared to the urban counties, but other researchers provide contradict results (Bennett & Probst, 2016; Clement et al., 2018; Bennett et al., 2019). Therefore, there is a need to further assess whether there are differences in 30-day hospital readmission between rural and urban long-term care hospitals. The assessment could provide important insights that could be used by relevant stakeholders to improve access to quality care among the elderly specifically in Tennessee's rural areas, where there are concerns issue is quality and access to long-term care via the Medicaid expansion program.

Purpose of the Study

The purpose of this quantitative descriptive study is to determine whether differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. The independent variable was hospital location, which is a dichotomous variable consisting of two options urban or rural. The dependent variable was the 30-day admission rates, which was scored on a continuous scale. The covariate variables that will be considered include gender and insurance coverage.

Research Question and Hypotheses

The study addressed one research question and the associated hypotheses listed below.

RQ1: Using 2019 annual data, is there a significant difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

$H1_0$: There is no statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge.

$H1_1$: There is a statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge.

Conceptual Framework

The conceptual framework that guided this study's assessment of the difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge is the Donabedian framework. In 1966, Avedis Donabedian developed the framework, which was therefore named after him (Donabedian, 1966). Avedis was a physician and a professor of Public Health and in 1965 actively participated in the review of the quality of public health after the enactment of the Medicare and Medicaid programs (Ayanian & Markel, 2016).

According to the Donabedian framework, the quality of health care be established based on information from three aspects of healthcare that include the structure, process, and outcome (Donabedian, 1966). The structure defines that approaches used to deliver care (Donabedian, 1966). The Donabedian framework identifies some of the structural factors that include hospital's facility, qualifications of care providers, human resources, accounting, and material resources (Donabedian, 1966). According to the Donabedian framework, the process refers to the aspects related to the engagement between the patients and the healthcare providers during the delivery of care. The process therefore includes all the components of the care delivery (Donabedian, 1966). The process measures focus on how the healthcare system work to deliver the outcome. As noted by McCants et al. (2019), it is vital for the healthcare providers to be knowledgeable to coordinate services effectively for their patients. The outcome refers to the impact of the provided healthcare on the health status of the patient. Therefore, the outcome describes the impact on the patient. Some of the outcomes could include recovery, death, readmission, survival and regain of health (Ibanez, 2021; Swilling, 2020).

Various researchers have used the Donabedian framework in studying aspects related to the 30-day readmissions (Ibanez, 2021; McCants et al., 2019; Swilling, 2020). Swilling (2020) used the Donabedian framework in the assessment of the relationships between insurance primary payer’s status, demographic characteristics, and 30-day readmission rates among patients with diabetes. Using the framework, Swilling identified the insurance coverage and payer status as the aspects associated with the structure while the 30-day readmission rates were considered as the outcomes. Moore et al. (2015) also utilized the Donabedian framework and identified the readmission rates as the trauma care outcomes. McCants et al. (2019) also used the Donabedian framework in the assessment of the impact of integrated case management services where the impact was assessed based on the rate of readmissions. Ibanez (2021) utilized the Donabedian framework in the analysis of how the use of health navigators' impact on the rate of readmissions for female emergency department patients.

The Donabedian theoretical model is well aligned with this study. In the context of this study, the outcome measures can be interpretated as the preventable hospital readmissions 30 days after discharge. The structure measures can be interpreted as the characteristics of urban and rural long-term care hospitals are directly related to care outcomes (30-day readmission rates). The process measures focus on the interaction between the healthcare personnel in the urban and rural long-term care hospitals in addressing the challenges associated with readmission.

Nature of the Study

The nature of the study was quantitative, guided by descriptive design. In this study, I adopted the quantitative methodology because it offered an opportunity of conduct an objective analysis of the research topic (see Bruce et al., 2018). As noted by Ratelle et al. (2019), quantitative methodology allows the use statistical techniques such as *t* tests, which determination of statistically significant findings that can be generalized. Therefore, the quantitative methodology enabled me to explain whether there was a difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge using *t*-test analysis. It should also be noted that the adoption of the quantitative approach enabled me to limit the occurrence of errors and biases experienced when using qualitative approaches (Bruce et al., 2018).

The adopted quantitative method will be based on descriptive research design, which allowed me to determine the status of 30-day readmissions to hospitals in the urban and the rural long-term care hospitals in Tennessee without manipulating any of the variables. The population of focus consisted of patients who experienced 30-day readmissions in urban and the rural long-term care hospitals in Tennessee. I retrieved the secondary data from the CMS website (https://data.cms.gov/provider-data/dataset/fp6g-2gsn). The data are publicly available and were published by the CMS, therefore, the data were expected meet the required high standards. I conducted multiple linear regression to assess for whether being an elderly from rural long-term care hospitals predicted the likelihood of being readmitted 30 days after discharge. I assessed and controlled for the effect of primary payer status (Medicare, Medicaid, uninsured, or private insurance) on the 30-day readmissions. I also examined the demographic characteristics such as age, gender, and income as potential moderators in the difference in the preventable hospital readmissions 30 days between urban and rural long-term care hospitals in Tennessee.

Literature Search Strategy

The literature used to review the evidence related to key variable and concepts was retrieved from various databases. I consulted the following research databases: PubMed, CINAHL Plus, BioMed Central., ProQuest, EBSCO, and CMS. I also searched Google Scholar. My search focused on previous evidence of 30-day readmission rates, access to health among the elderly in rural and urban setting, readmission rates in long-term care hospitals, and Medicaid interventions geared towards addressing challenges of access to care among the elderly. The search in the identified databases was carried out using key search terms that included *readmission rates*, *rehospitalization*, *30-day readmission*, *access to health*, *elderly*, *rural long-term care hospitals*, *rural health facilities*, *urban long-term care hospitals*, *urban health facilities*, *Medicaid*, and *Donabedian framework*. I combined the highlighted key terms using Boolean operators such as AND, NOT, and OR. Using the developed search string, I obtained a total of 1,374 articles, which I further subjected to a selection process that involved scrutiny of the year of publication, relevance, and perceived quality of the research conducted. I confined the selection of the literature review to articles published between 2017 and 2022, with exception of seminal studies that provided important historical perspective. Only peer-reviewed studies were included. The titles of the articles, the abstract and full text were analyzed to determine relevance, which resulted in the scaling down of the search outcomes to 78.

Literature Review Related to Key Variables and/or Concepts

Healthcare Outcomes Among the Elderly in Rural and Urban Areas

The U.S. population is rapidly ageing, and it is expected that by 2030 about 25% of the U.S. population will be over 85 years of age (Ko et al., 2019). The population of Americans aged above 65 years is expected to increase from 47.8 million in 2015 to about 87.9 million in 2050 (Harris-Kojetin et al., 2019). By 2030, Americans aged 65 years or older will be more than younger population (64 years and less; Fulmer et al., 2021). Foutz et al. (2017) reported that the majority of the rural population is made up of elderly (65 years and older) individuals. With the increasing number of older adults comes the increasing susceptibility to chronic diseases and various comorbidities (Dai et al., 2021; Esme et al., 2019). Jensen et al. (2020) noted that the rural United States have a large proportion of older and sicker people.

Kosar et al. (2020) carried out a retrospective cohort study that involved analysis of Medicare beneficiaries of old people aged 66 years and above who were admitted to 4738 hospitals for chronic diseases. One of the aims of Kosar et al.'s (2020) study was to assess whether there was difference in readmission rates between rural and urban settings. Based on the assessment of 1,538,888 hospitalizations from urban counties and 182,983 hospitalizations from urban non-adjacent rural counties, Kosar et al. (2020) reported that the 30-day readmission rates were 0.4 (95% CI [0.2, 0.6]) percentage points higher for the rural counties compared to the urban counties.

Ko et al. (2019) analyzed the frequency and outcome of emergency department utilization among people aged 60 years and more residing in the urban and rural areas. The researchers based their observations on a population-based study that involved analysis of data from health insurance database. Using multivariate logistic regression analysis, Ko et al. reported 29.75% (n = 1879) utilization of emergency department in the rural areas compared to 28.07% (n = 908) in the urban area. However, the researchers noted that the reported difference was not statistically significant. But Ko et al. reported that compared to the urban population, the risk of emergency department visits with a high acuity was higher in the rural areas.

There are various factors that could explain the highlighted difference in healthcare access among rural and urban populations. Foutz et al. (2017) noted that Americans living in rural counties face significant health challenges relating to access and healthcare coverage. According to Mandal (2022), rural Americans have higher risk of suffering from chronic conditions compared to their urban counterparts. The barriers to healthcare access faced by people living in the rural areas include shortage in providers, closure of rural hospitals, and long travel distance to find healthcare providers (Foutz et al., 2017). Another concern in the rural areas is the rate of hospital closure. According to Germack et al. (2019), recent years have been marked by increasing rates of hospital closures in rural communities. In the past decade, about 100 rural hospitals closed. The closure of hospitals in the rural areas has negative effect on residents’ access to important hospital-based services (Germack et al. 2019). Factors associated with the closure of hospitals in the rural areas include the limited funding, lack of sufficient and update facilities, low occupancy, and unsustainable financial health (Germack et al. 2019). The closure of hospitals has a negative effect on the access to health services among the people residing in the rural areas. Germack et al. carried out a study that assessed how the rural hospital closures influence the supply of physicians across different specialties. Based on the analysis of the data obtained from Area Health Resources Files for the period 1997–2016, Germack et al. found that rural hospital closures resulted in an 8.3% decline in the supply of general surgeons. The researchers also noted that the closure of the hospitals was characterized by the reduction in the supply of surgical specialists, physicians and particularly the primary care physicians.

The factors associated with the community that include the employment status, poverty, and the insurance status may also determine the hospital closure. Foutz et al. (2017) noted that demographic characteristics of individuals living in rural areas in the

US include high rates of unemployment and low-income status. Compared to the urban population, people living in rural areas have low level of education with less than 20% of them having a bachelor's degree or higher compared to about 40% in the urban areas (Foutz et al., 2017). The highlighted difference in the demographics between the urban and rural is also reflected in their access to health.

According to Fulmer et al. (2021), about 24% of the community-dwelling older adults face the challenge of social isolation that could impact negatively on the psychological wellbeing. Such older adults also face mistreatment and abusive relationship that further increases the sense of social isolation. To address social isolation, interventions such as provision of in-home support and innovative housing options, and recreational opportunities should be considered (Fulmer et al., 2021). Garcia et al. (2019) assessed the mortality data for U.S. residents from the National Vital Statistics System to determine the potentially excess deaths among the elderly. Garcia et al. defined the elderly as the individuals aged above 80 years. The researcher noted that there was a higher percentage of potentially excess deaths in rural counties, which increased between 2010 and 2017.

It should be noted that some studies have indicated that rural culture, which is characterized by strong sense of connectedness among residents may contribute to reduced cases readmissions (Clement et al., 2018). Clement et al. (2018) examined whether rurality is associated with 30-day hospital readmission rates. Based on a cross-sectional study that focused on the analysis of data from the CMS-NHC website, Clement et al. (2018) assessed 30-day risk-adjusted rehospitalization rates. The data provided insights into 30-day risk-adjusted rehospitalization rates for 2014-2015. Using multiple linear regression analysis, Clement et al. reported that rural areas and large rural towns register lower cases of readmissions compared to urban and suburban areas. However, the researchers recommended for further studies since they were the first to address the topic.

Long-Term Care Facilities

Long-term care providers play a vital role in ensuring delivery of quality care service to millions of people in the United States. According to Harris-Kojetin et al. (2019), in 2016 there were about 65600 long-term care service providers that included paid and regulated providers. Long-term care hospitals offer services that include a broad range of health and supportive services needed by frail elderly people whose capacity for self-care is limited due to chronic illnesses, cognitive or mental disabilities and other health-related challenges (Harris-Kojetin et al., 2019). The ACA (2010) refers to long-term care facilities as long-term services and supports targeting health care-related and non-health care-related services (Harris-Kojetin et al., 2019). Long-term care facilities assist people with activities of daily living, and they also assist with instrumental activities of daily living along with health maintenance (Harris-Kojetin et al., 2019). Based on the analysis of data obtained from National Center for Health Statistics surveys of adult day services centers and residential care communities and 2015-2916 administrative records from the CMS on home health agencies, hospices, and nursing homes, Harris-Kojetin et al. reported that long-term care services serve over 8.3 million Americans. Harris-Kojetin et al. noted that the long-term care services include adult day services centers, home health agencies, hospices, nursing homes, assisted living and residential care communities.

The cost of long-term care is a growing concern for the elderly, and it is also a challenge faced by the state and federal governments (Harris-Kojetin et al., 2019). The financial burden associated with long-term care vary based on the type of paid care and the type of provider (Harris-Kojetin et al., 2019). The largest portion of the costs of long-term care is met by Medicaid financing followed by Medicare out-of-pocket payments and private sources (Nguyen, 2017). Evidence indicates that despite the fact that people of all ages may require long-term care services the risk of needing such services increases with the increasing age (Harris-Kojetin et al., 2019). It is projected that 50% of Americans attaining the age of 65 and above needs long-term care services averaging cost of $138,000 (Harris-Kojetin et al., 2019). Although the average length of long-term care services required by an individual is 2 years, the length is longer than 2 years for people turning 65 years and older (Harris-Kojetin et al., 2019). It is projected that the number of elderly Americans using long-term care services will gradually grow in the coming years (Harris-Kojetin et al., 2019).

Concerns have been raised about the workforce in long-term care facilities. Evidence indicates that 86% of nursing homes and 77% of assisted living providers reported deterioration in workforce situation (American Health Care Association & National Center for Assisted Living, 2021). The report further indicated that about 99% of nursing homes in the United States face staff shortage. With the shrinking staff the long-term care facilities require the available staff to work overtime an extra shift

(American Health Care Association & National Center for Assisted Living, 2021). The report additionally indicated that the nursing homes face a challenge in hiring new staff, which could be linked to the lack of qualified candidates and lack of unemployment benefits (American Health Care Association & National Center for Assisted Living, 2021). Gandhi et al. (2021) also reported high turnover of nursing staff nursing homes. Based on the analysis of data from 15,645 nursing home facilities, Gandhi et al. noted that the turnover was as high as 94% and that the high turnover of nurses in nursing homes could negatively affect the delivery of quality care.

Medicaid Approaches to Address the Access to Quality Care Among the Elderly

Fulmer et al. (2021) identified key factors that need to be addressed for the United States to adequately prepare for the anticipated increase in the burden associated with caring for the elderly. To effectively address the healthcare challenges that come with ageing, there is a need to put in place an adequately prepared workforce. Fulmer et al. noted that the CMS should strategically put in place interventions to support the creation of a robust, qualified workforce across the various settings. Fulmer et al. also recommended the strengthening of public health for older adults and aligning the public health community-level services sector functions with the needs of the elderly. Fulmer et al. also noted the need to remediate disparities and inequities through the expansion of coverage via Medicare Advantage plans to include all older adults.

The 2010 ACA expanded Medicaid to enhance insurance health coverage for low-income adults (McInerney et al., 2020). The literature examining the impact of Medicaid expansion on insurance coverage and access to care by low-income individuals show positive effects of the expansion (Gruber & Sommers, 2019; Guth et al., 2020). McInerney et al. (2020) noted that the Medicaid expansion offered accessible and low-cost coverage options which increased the number of people with health insurance. The expansion targeted the older adults who are less healthy and therefore have challenges accessing other coverage, especially low-income adults without sufficient resources to afford the expensive private insurance or Medicare. However, according to McInerney et al., there is inconclusive evidence regarding the impact on Medicaid expansion on the health status of the low-income individuals.

One in every five Americans now benefit from the Medicaid program. As of 2017, it was estimated that the Medicaid program cost was about $600 billion (Franco Montoya et al. 2020). By 2017, 31 states including District of Columbia had taken up Medicaid expansion. The other states opted out of the Medicaid expansion program following the Supreme Court ruling that made the program optional (Mandal, 2022). The ACA has taken various steps to ensure that the increased demand for healthcare is met with adequate number of primary care providers (Mandal, 2022). Some of the steps taken include expanding the capacity of community health centers serving low-income patients and improving the providers capacity through recruitment and retention initiatives targeting new primary care providers in underserved areas (Wishner & Burton 2017). The Medicaid payment rates were also temporarily increased for primary care services (Zuckerman et al., 2017). Mandal (2022) carried out an analysis of rural-urban differences in access to healthcare. The researcher focused on insurance cover the access to primary providers access to preventative care and use of emergency departments.

According to Mandal, Medicaid expansion resulted in greater reduction in uninsurance among low-income rural individuals compared to their urban counterparts.

Medicaid influences the quality of care among the elderly by influencing the health care providers. Some researchers have examined how Medicaid expansion has impacted on health care providers with evidence indicating the reduction in uncompensated care costs to healthcare providers as the main motivation. As noted by Nikpay et al. (2016), the Medicaid expansion resulted in a 50% reduction in uninsured hospitalization. Evidence also indicated that Medicaid expansion resulted in a 30% reduction in hospital uncompensated care (Blavin, 2016). Medicaid expansion also coincided with increase in hospital stays being paid by Medicaid, but the payment was done at lower level compared to private insurance which resulted in lower financial gains to hospitals (Young et al., 2019). However, since Medicaid reduced uncompensated care, hospitals still were able to adjust the improvement in the net margins despite the reduction in financial gains due to the lower level (Blavin, 2016). The net gains were reported in states that adopted Medicaid expansion compared to no expansion states (Gruber & Sommers, 2019).

However, evidence suggests that Medicaid expansion introduced concerns regarding the access to care (Gruber & Sommers, 2019). Researchers indicated that with the expansion of Medicaid the demand for healthcare increased but the supply did not (Cole et al., 2017; Gruber & Sommers, 2019). The failure of the supply to match the demand was associated with the fact that some providers are unwilling to accept Medicaid patients because of lower reimbursement rates compared to those for private insurance and Medicare (Decker, 2012). However, it should be noted that evidence is mixed regarding whether the expansion resulted in reduced access because some researchers indicate increase in wait lines following Medicaid expansion (Miller & Wherry, 2017) whereas others did not report any change (Neprash et al., 2018; Tipirneni et al., 2015). As noted by Gruber and Sommers (2019), the influence of Medicaid expansion on provider availability is important because it informs the overall benefits of the program regarding access to care especially in low-income areas. In federally qualified health centers, it is important to ensure that Medicaid expansion does not result in overwhelming the center's capacity (Cole et al., 2017).

Bucholz et al. (2020) noted that compared to private insurance patients, the Medicaid patients have higher rates of 30-day readmissions. Based on the analysis of data retrieved from 2010 to 2017 showing the trends in 30-day readmission rates for Medicaid and Private insurers, the researchers concluded that there is disparity in the readmissions based on insurance status. It should be noted that Bucholz et al. focused on patients with chronic conditions. However, Bailey et al. (2019) noted that the readmission rates for Medicaid patients remained relatively stable between 2010 and 2016. But in 2016 the readmission rates were high among Medicaid patients aged between 45 to 64 years.

Various approaches have been taken under the ACA to reduce the hospital readmission and the associated costs. The CMS Hospital Readmissions Reduction Program focuses on motivating hospitals to reduce readmission by tying Medicare admissions payments to hospital readmission rates (James, 2013; Joynt & Jha, 2013). The program was launched in 2012 as a Medicare value-based purchasing program (James, 2013; Joynt & Jha, 2013; McIlvennan et al., 2015) and seeks to motivate hospitals to reduce readmissions by encouraging them to enhance communication and care coordination to achieve enhanced engagement between patients and caregivers on discharge plans to avoid preventable readmissions. The Hospital Readmissions Reduction Program therefore supports the national goal of tying payment to quality care (Gu et al., 2014; James, 2013; Joynt & Jha, 2013). As noted under Section 1886(q) of the Social Security Act, the Secretary of the U.S. Department of Health and Human Services has the power to cut payment to certain hospitals because of excessive readmissions (James, 2013; Joynt & Jha, 2013). The Hospital Readmissions Reduction Program targets specific conditions that include acute myocardial infarction, chronic obstructive pulmonary disease, heart failure, pneumonia, coronary artery bypass graft surgery, and elective primary total hip arthroplasty and/or total knee arthroplasty (McIlvennan et al., 2015). As noted by Chakraborty et al. (2017), about 2,600 hospitals received financial penalties that included reduction of the CMS reimbursements due to high readmission ratios, which demonstrates the importance of 30-day readmission as an important metric for reducing readmission costs and promoting the quality of care in the United States.

The other program developed by CMS to address the issue of hospital readmission and cut the associated costs is the Community-Based Care Transitions Program that is anchored within the ACA (Evans et al., 2021). The Community-Based Care Transitions Program aims to reduce the 30-day hospital readmission rates by 20%. The Community-Based Care Transitions Program include community-based organization that rely on in hospital or in home visits while others adopt phone-based services with the patients as a means of helping them to transition and reduce readmissions. Evans et al. (2021) assessed the effectiveness of Community-Based Care Transitions Program by focusing on Chicago Southland Coalition for Transition Care. The researchers noted that the program utilizes social workers to help patient to transition and focus on addressing non-medical obstacles. Based on difference in difference model and the analysis of Medicare discharges between 2010 and 2015, Evans et al. observed that the program reduced 30-day readmission rates by 14%. Evans et al. further noted that the reduction in 30-day readmission rates also led to reduced healthcare costs.

Kocakulah et al. (2021) provided an in-depth analysis of the steps taken by Medicare to reduce the cost by addressing hospital readmissions. The readmissions reduction program that was initiated in 2012 sought to address the excess hospital patient readmissions and the associated costs. In 2013, about 18% of the Medicare patients were readmitted with 30 days. According to CMS, the readmission resulted in additional cost amounting to $26 billion and $17 billion were preventable (Kocakulah et al., 2021). Ferro et al. (2019) noted that the implementation of Hospital Readmissions Reduction Program resulted in significant reduction in readmission for Medicaid patients as well as Medicare patients. However, Ferro et al. still observed high rates of 30-day readmission among Medicaid patients compared to the Medicare patients. Ferro et al. based their observations on difference-in-difference analysis of data obtained from Nationwide Readmissions Database that included Medicare, Medicaid, and Private insurance patients.

Challenge of Hospital Readmission Among the Elderly

As noted by Rubin et al. (2017), the 30-day readmission is now an important measure of care quality and used for interventions geared towards reduction of healthcare costs. The adoption of the 30-day readmissions by CMS under the Hospital Readmission Reduction Program began after the implementation of the ACA (Ostlling et al., 2017). The 30-day readmission measures focus exclusively on the unplanned readmissions occurring within 30 days after discharge regardless of cause or primary diagnosis. The 30-day readmission is used by the CMS to evaluate the performance of the hospitals where evidence of excess readmission ratio result in financial penalty (Rubin et al., 2017).

Murray et al. (2021) assessed the specific socio-demographic and economic factors that influence the 30-day readmissions by focusing on the conditions targeted by the CMS Hospital Readmission Reduction Program. Murray et al. (2021) based their analysis on the data obtained from Nationwide Readmissions Database. The researchers noted that the factors associate with increased cases of 30-day readmission include the income level with the patients in the lowest income quartile registering increased likelihood of readmission. However, Murray et al. (2021) noted that rural hospital designation is associated with reduced odds of 30-day readmission. The researchers noted that the reported trends were evident even among the patients aged 65 years and above.

Goto et al. (2017) reported that the 30-day readmissions was higher among individuals aged above 65 years. Goto et al. (2017) based their observations on retrospective cohort study that involved the analysis of 2006-2012 data obtained from the

State Inpatient Database of eight geographically dispersed US states. The researchers primarily focused on any-cause readmission within 30 days of discharge. Following the analyses of data using unadjusted and adjusted logistic regression models with stratification by age (40–64 years and ≥65 years), Goto et al. (2017) reported that among individuals aged above 65 years, the readmission within 30 days was between 63%–65%. Berry et al. (2018) also noted that the likelihood of readmission is higher among the elderly patients. It should however be noted that Berry et al. (2018) focused on the patients with multiple chronic conditions. Berry et al. (2018) based their observations on a retrospective analysis of the 2013 index hospital admissions retrieved from the US Agency for Healthcare Research and Quality Nationwide Readmissions Database.

Schreckinger et al. (2021) also reported high odds of readmission among older adults. According to the researchers, individuals aged above for 65 years with epilepsy have higher odds of readmission. Schreckinger et al. (2021) based their research on data from the 2014 Nationwide Readmissions Database. The researchers compared 30-day readmissions and causes of readmissions among elderly (aged above for 65 years) individuals with epilepsy and between the elderly and young (18–64 years old) patients. Schreckinger et al. (2021) highlighted some of the causes of readmission that included septicemia, congestive heart failure, complications of surgical procedures or medical care, pneumonia, cardiac dysrhythmias, acute and unspecified renal failure, Chronic obstructive pulmonary disease and bronchiectasis and gastrointestinal hemorrhage. Schreckinger et al. (2021) also reported the healthcare utilization and outcome at 30-day readmission among the older adults that included death in hospital., transfers, high cost and discharge against medical advice.

Shebehe and Hansson (2018), reported that the rates of 30-day hospital readmission for patients aged 65 years and above is high among individuals living in low socioeconomic status neighborhoods. Shebehe and Hansson (2018) based their observation on cross-sectional ecological stud involving 283,063 patients from 29 primary health care centers in Sweden. The researchers observed that the lack of employment explained up to 71.4% of the variability in the 30-day hospital readmission. Shebehe and Hansson (2018) therefore concluded that social economic status should be considered as an important parameter when assessing 30-day hospital readmission among the elderly.

Literature identifies various approaches that can help to address hospital readmissions among the elderly. Spiers et al. (2019) carried out as systematic review and metanalysis involving 12 studies and observed that the availability of nursing and residential care reduces case out of hospital readmission among the elderly. Burhenn et al. (2020) highlighted the importance of carrying out laboratory diagnosis before discharge to reduce hospital readmission within 30 days of discharge. Based on a matched case-control study involving 184 case-patients (≥ 65 year) readmitted within 30 days after discharge, Burhenn et al. (2020) reported 3 times increase in risk of readmission among the patients with at least 2 abnormal laboratory results. The researchers therefore recommended for routine determination of the laboratory values before discharge. Glans et al. (2020) carried out a comparative retrospective study to identify patients with high risk of readmission within 30 days of discharge and approaches to reduce such readmissions. Based on the data collected from 720 older patients, Glans et al. (2020) observed that patients with poor health and using multiple medications are at a greater risk of readmission to hospital is within 30 days of discharge.

Bennett et al. (2019) also examined the factors that determine the readmissions among Medicare patients initially presenting at rural facilities. The researchers based their study on the data from the 2013 Medicare Claims file. Compared to the patients presenting at the urban hospitals, Bennett et al. (2019) found that the rate of 30-day readmission was low in the rural hospitals. Bennett & Probst (2016) conducted a cross-sectional analysis of Medicare claims with the aim of determining the readmission rates and factors affecting readmission. Compared to the urban dually eligible beneficiaries, Bennett & Probst (2016) reported that the rural dually eligible beneficiaries had lower rates of 30-day readmission. The researchers noted that the readmission rates could be reduced by adopting a 30-day physician follow-up, which they also noted to be higher among the rural residents.

Evidence suggests that the availability of primary care follow-up following discharge could help to reduce Medicaid readmission. In a retrospective cohort study that involved the assessment of 2580 hospitalization of patients, Wiest et al. (2019) concluded that facilitated primary care follow up one week after hospital discharge resulted in reduced cases of Medicaid readmissions. Misky et al (2018) noted that there is a wide range of factors influencing hospital readmission. Misky et al (2018) carried out a qualitative study that sought to enhance the understanding of patient perspectives regarding why they returned to the hospital after discharge. The study included 18 Medicaid patients who had returned to the hospital 30 days after they were discharged from a major metropolitan hospital. Misky et al (2018) reported that some of the factors that contribute to the high likelihood of patients to return to the hospital after discharge include therapeutic misalignment, social fragility, access failure, and the disease behavior. According to the researchers, enhanced patient-provider trust and engagement during decision making along with addressing of social determinants could help to reduce hospital readmissions.

Van der Does et al. (2020) noted that readmissions 30 days after discharge could be reduced by addressing diagnostic, medication, or management causes. Based on a prospective cross-sectional single-center study that focused on 430 patients from an urban teaching hospital in Amsterdam, the Netherlands, van der Does et al. (2020) observed that 30% of the preventable readmissions within 30 days after discharge are caused by diagnostic problems while 27% are caused by medication problems and another 27% caused by management problems. According to Uitvlugt et al. (2021), 40% of the readmissions within 30 days after hospital discharge are preventable. Based on a cross-sectional observational study in which 1,111 cases of readmission were assessed, Uitvlugt et al. (2021) noted that 16% of them were as result of medication related problems. Uitvlugt et al. (2021) therefore recommended medication related intervention to put in place to reduce cases of preventable readmissions. Auerbach et al. (2016) carried out an observational study involving 1000 general medicine patients who were readmitted 30 days after they were discharged between 2012 and 2013 in 12 US academic medical centers. Some of the causes of frequent 30-day hospital readmissions include inadequate post-discharge follow-up, lack of discussions about care goals, premature discharge and patients lacking information on who to reach out to after discharge (Auerbach et al., 2016).

Definitions

30-day readmission: Refers to the unplanned readmissions occurring within 30 days after discharge regardless of cause or primary diagnosis (Kocakulah et al., 2021; Rubin et al., 2017).

Elderly: refer to people aged 65 years or more (Goto et al., 2017; Harris-Kojetin et al., 2019; Schreckinger et al., 2021).

Long-term care hospitals: Refers to the hospitals that provide long-term services and support targeting health care- related and non-health care-related services (Harris-Kojetin et al., 2019)

Assumptions

The assumptions refer to the aspects of the study that the researcher is not able to control but need to be true for the study to be relevant (Theofanidis & Fountouki, 2018). Given that this study relies on the archival data published by the CMS, it is assumed that the data is representative of the target population. The highlighted assumption is based on the understanding that the CMS collect the data nationwide. It is important to have representative data to ensure that the study outcome is applicable to the target population. I also assumed that no biases or errors were committed during the recording of the data. This assumption is critical because it determines the quality the research findings in terms of validity and reliability. I assumed that no biases or errors were committed because the CMS hire specialists who carry out data collection and documentation.

Scope and Delimitations

Delimitations refer a study that limit the scope of the study and describe the boundaries of a given study (Theofanidis & Fountouki, 2018). In this study, the research problem is that it is not known if differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. It is therefore evident that I only focused on the 30-day readmission rates and not any other types of readmissions such as 7-day readmission. The 30-day readmission was chosen because it is an important measure of quality and is associated with increased cost of care (Rubin et al., 2017). It should be noted that CMS use the 30-day readmission rates to evaluate the performance of the hospitals (Rubin et al., 2017). It is also evident from the research problem that the study only focuses on long-term care hospitals. The focus exclusively on long-term care hospitals is informed by the fact that most older people suffer from more than one serious condition and may need longer hospital stays following transfer from an intensive or critical care unit (Jensen et al., 2020). The choice of long-term hospital care was also informed by the high cost of long hospital stays and therefore the need to reduce readmission (Joynt & Jha, 2013; Evans et al., 2021).

It is also evident from the research problem that the study focuses on urban and rural long-term care hospitals which is important in providing insights into potential differences. Evidence suggests that urban and rural health facilities differ in terms of available infrastructure and workforce which may influence the quality of care and possibly the readmission rates (Rubin et al., 2017; Meurs et al., 2021). The study focuses exclusively on Tennessee because the state has high number of aging people and the State if focused on making the life of elderly satisfactory (Tennessee Commission on Aging and Disability, 2019). It is therefore expected that the outcome of this study will be generalizable to the elderly in urban and rural long-term hospital care in states that have similar demographics and healthcare systems as Tennessee.

Limitations

Limitations are weaknesses inherent in each study that is out of the control of the researcher (Theofanidis & Fountouki, 2018). One of the limitations is associated with the use of archival data. The adopted methodological approach restricts me to use archival data which therefore removes the freedom to obtain further data that could be used to develop additional insights into the research topic. As noted from the research question, I focus on the data that was collected from in 2019 since it is the most recent data that is available. Therefore, it means that I will be limited to base the conclusions on dated data that may not reflect the existing situation particularly given the possible effect of COVID-19 on the existing dynamics regarding hospital readmissions. To mitigate the limitations associated with the use of archival data, I will conduct extensive research of secondary sources to fill gaps that are not well addressed. The other limitation associated with his studies related to the use of quantitative methodological approach. Using the quantitative methods limited my ability to obtain qualitative data such as participants experiences regarding hospital readmissions. It should however be noted that based on the research question, quantitative data was required for this data.

Significance

This study has various contributions advancing knowledge, practice, and policy. The outcome of the study also has potential positive social change implications. Concerning the contribution of the study in advancing knowledge in the discipline, the outcome of this study he is expected to address the gap existing in the literature regarding the difference in 30-day readmission rates among the elderly between rural and urban long-term care hospitals. it should be noted that some studies indicate that the 30-day readmission rates among the elderly is high in the rural hospitals compared to urban hospitals (Kosar et al., 2020) but others contradict (Bennett & Probst, 2016; Bennett et al., 2019, Clement et al., 2018).

Concerning the contribution of the study towards practice and policy, it is expected that the outcome of the study will equip the relevant stakeholders with up-to-date information regarding 30-day readmissions in urban and rural long-term hospitals. With the insights from the study outcome, the policymakers will be able to put in place strategies to minimize the readmissions and the associated costs and health concerns. This is important because the 30-day readmission rates are considered one of the indicators of quality care and a determinant of cost of care (Meurs et al., 2021; Rubin et al., 2017; Wish, 2014).

The outcome of this study is also expected to have a positive social change implications on the well-being of the elderly. It should be noted that the elderly makes the highest proportion of the Americans living with multiple complications that often require admission in long-term care hospital (Jensen et al., 2020; Shebehe & Hansson, 2018). By contributing towards reduced 30-day readmission rates, it is expected that the study will help in enhancing quality of life among the aging while also reducing burden to healthcare facilities.

Summary and Conclusions

This section provided and in that assessment of the existing literature relating to the 30-day readmission among the elderly in rural and urban health care facilities. It is evident from the literature that the United States needs to focus on the elderly as the population increases. given the increased susceptibility of the elderly to multiple infections, long-term Care hospitals become importance. However, it is evident that hospital stays is associated with high cost of care and increased pressure on the available health resources. Addressing the frequency of readmission text specially the 30-day readmission rates is important in bringing down the cost and ensuring quality care. The source of literature indicates that Medicaid have played a critical role in ensuring increased access to care among the elderly. It is also evidence that Medicaid is taking steps to reduce 30-day readmission rates to promote the quality of care and reduce costs.

However, the literature suggests that there is a gap regarding whether there is a difference in 30-day readmission rate among the elderly in urban and rural settings. According to Kosar et al. (2020), the 30-day readmission rates are higher among Medicare beneficiaries in the rural counties compared to the urban counties, but other researchers provide contradict results (Bennett & Probst, 2016; Clement et al., 2018; Bennett et al., 2019). Therefore, there is a need to further assess whether there are differences in 30-day hospital readmission between rural and urban long-term care hospitals. The assessment could provide important insights that could be used by relevant stakeholders to improve access to quality care among the elderly specifically in Tennessee's rural areas, where there are concerns issue is quality and access to long-term care via the Medicaid expansion program. Section 2 describes the research methods used in this study to address the highlighted gap.

Section 2 – Research Design and Data Collection

Introduction

The purpose of this quantitative descriptive study was to determine whether there are statistically significant differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. Guided by the highlighted purpose, the study addressed the research problem that it is not known if differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. The study's focus on the elderly is vital given the expected rise in the population of the people aged 65 and above years in the United States (Fulmer et al. 2021). Therefore, the outcome of the study will offer insights that relevant stakeholders would use to improve access to quality care among the elderly specifically in Tennessee's rural areas, where there are concerns regarding the quality and access to long-term care via the Medicaid expansion program.

This section provides the methodological approach used in the collection and analysis of data to address the highlighted purpose of the study. The first section describes the research design and the rationale focusing on the variables, and the justification of the adopted research design based on how it aligns with the research question, available time and resources, and suitability in advancing knowledge in the discipline. The second section is the methodology where the population is defined, sampling and sampling procedures are described, and instrumentation and operationalization of the constructs are very good. The third section focuses on threats to validity, which also includes a discussion of ethical procedures. The final section is a concise summary of the described design and methodology.

Research Design and Rationale

This research considered one independent variable, one dependent variable and two covariables. The independent variable is the hospital location, which is a dichotomous variable consisting of two options urban or rural. The dependent variable is the 30-day readmission rates, which will be scored on a continuous scale. The 30-day readmission rate was chosen because it is considered an indicator of whether a hospital is doing its best to offer quality care in the prevention of complications, provision of discharge instructions and assistance to the patient during transition from hospital to home based care (Meurs et al., 2021; Rubin et al., 2017; Wish, 2014). The covariate variables were gender and primary payer status.

The methodological approach that guided this study was the quantitative methodology based on descriptive design. I adopted the quantitative methodology because it offered an opportunity to conduct an objective analysis of the research topic (see Bruce et al., 2018). As noted by Ratelle et al. (2019), quantitative allows the use of statistical techniques such as *t* tests, which facilitates the determination of statistically significant findings. The statistically significant outcome is then used to generalize and conclusive determinations and recommendations regarding the research topic. In contrast, I concluded that it would have been unrealistic to adopt the qualitative methodologies because of their subjective nature, which advocates for the consideration of multiple truths, therefore, not allowing obtaining of conclusive insights (Salvador, 2016).

Additionally, I did not consider the qualitative methodologies because such approaches focus on the respondents' experiences and feelings, which are highly influenced by the context and vary from person to person (Salvador, 2016). Therefore, by adopting the quantitative methodology, I was able to explain whether there are statistically significant differences between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge using *t*-test analysis and multiple linear regression. It should also be noted that the adoption of the quantitative approaches enabled me to limit the occurrence of errors and biases experienced when using qualitative approaches (Bruce et al., 2018).

Quantitative methodologies consist of various designs, but for this study, I used the descriptive design. The chosen design was deemed appropriate because it focuses on the discovery of new meanings and the determination of the existence and frequency of events (Bloomfield & Fisher, 2019). The descriptive design approach is guided by questions of "how" and "who," which allowed me to identify problems existing in practice (Bloomfield & Fisher, 2019). In this study, the use of descriptive design allowed me to examine how the rate of potentially preventable hospital readmissions 30 days after discharge in urban long-term care hospitals compares to the readmission rates in rural long-term care hospitals in Tennessee. The use of descriptive design also allowed me to utilize secondary data in answering the research question. Using the secondary data from CMS (https://data.cms.gov/provider-data/dataset/fp6g-2gsn) enabled me to circumvent the challenges associated with the resources and the time required to carry out primary research. The highlighted data are freely available for public use and there is no cost associated with its use.

I was guided by the positivist paradigm in the implementation of the highlighted quantitative method based on the descriptive design. The positivist paradigm was important in enabling the study to adopt the methodological approaches that would allow the determination of the universal truth regarding the research questions. As indicated by Park et al. (2020), the positivist paradigm assumes the presence of universal and generalizable truth regarding research phenomena. Therefore, concerning this study, the positivist paradigm guided my approach in designing and the implementation of the methodology by focusing on the approaches that facilitate the determination of whether statistically significant difference exists in the admission rates between urban and rural hospitals in Tennessee. The adoption of the positivist paradigm also allowed me to implement approaches that enhance the applicability of the research findings. Guided by the positivist paradigm, I also implemented approaches that would enhance the study's validity, reliability, and representativeness (see Salvador, 2016). Using the positivist paradigm, I ensured that the sampling approaches were representative. Random samples obtained from the secondary data were used. I also ensured that a representative sample size was utilized, which was obtained through a priori analysis using a power calculator.

Methodology

Population

The general population of interest for this study is made up of the patients in urban and the rural long-term care hospitals in Tennessee. The highlighted general population is deemed appropriate since the research question focused on the difference in the 30-day readmissions between urban and rural long-term care hospitals. The population include the patients of both gender groups and with various primary payer status. From the stated general population, the target population included patients in urban and the rural long-term care hospitals in Tennessee whose readmission data have been documented in the CMS database (https://data.cms.gov/provider-data/dataset/fp6g-2gsn). The targeted CMS database was last updated on the July 28, 2022, and it contains data on the quality of patient care measures in long-term care hospitals compare. The database has a total of 492,480 patient entries from different states across the United States of America.

Sampling and Sampling Procedures

The inclusion of patients in the CMS unplanned hospital visits dataset was based on purposive sampling approach. The readmission data for the patients who met specific criteria during their initial visits were documented. The 30-day readmissions considered were for the patients who may have returned to the same hospital or to a different hospital. The database also considered readmissions among the patients who may have been readmitted for a condition that is related to their recent hospital stay, or for an entirely different reason. The database contains readmission measures for individuals aged 65 or older who were Medicare beneficiaries and had enrolled in Medicare not less than 12 months prior to their hospital admission and continued with the enrollment throughout 30 days after their original discharge. The database excludes the patients who died during the index admission and those who did not follow medical advice in making the decision to leave the hospital. The data on the unplanned hospital visits contained in the CMS database were obtained from Medicare enrollment and claims data. Some measures also include Veterans Health Administration administrative data. Within the database, the unplanned hospital visits are measured within 30 and 7 days after visiting the hospital or following discharge. The 30-day readmission data provided on the website are calculated based on Medicare claims data and eligibility data. Additionally, 30-day readmission data is provided for patients with chronic obstructive pulmonary disease, heart attack, heart failure, pneumonia, and hospital-wide readmission.

I obtained random samples from the target defined population. I limited the analytic sample to (a) the patients aged 65 years and above and (b) patients readmitted in rural and urban long-term care hospitals 30 days after discharge. For this study, the 30-day readmission included all medical, surgical, and gynecological, neurological, cardiovascular, and cardiorespiratory hospital patients. The samples excluded patients who (a) had planned hospital visits 30 days after discharge, (b) were admitted 30 days after discharge due to accidents or new and unrelated conditions, (c) had not enrolled in Medicare not less than 12 months before hospitalization, and (4) did not maintain the enrollment throughout 30 days after their original discharge.

To gain access to the data, I searched the CMS website (https://data.cms.gov/provider-data/dataset/fp6g-2gsn). The data were then downloaded as CSV files and transferred to SPSS. As already noted, the data used in the study are from the U.S. government and in the public domain. Therefore, for this study, no permissions are required to gain access to the data. However, I will provide an attribution to the CMS as the source.

The CMS dataset used in this research is reputable and has been used by various researchers (Alghanem & Clements, 2020; Wong et al., 2020). The CMS provide in-depth explanation of the data sources and how they are obtained, and the approaches used in the calculation of the readmission rates, which enhances the reputability of the source. The determination of readmission included the veteran's health administration data. For accuracy in the documentation of 30-day readmissions, Medicare adjusts for risks based on patient characteristics and the likelihood of returning the hospital. The risk adjustment takes into consideration age, past medical history, and comorbidities reported during initial admission.

Sample size calculation was carried out using G*Power 3.1 calculation. It should be noted that for this study, I utilized *t* test and multiple linear regression to assess whether being an elderly person from rural or urban long-term care hospitals predicted the likelihood of being readmitted 30 days after discharge. For this study, sample size was determined a priori based upon a statistical power of 0.95 (see Faul et al., 2007). The alpha level statistical significance is set at 0.05. Since multiple linear regression analysis was utilized, an effect size of 0.15 was used. Considering the described parameters, the G*Power 3.1 calculation of sample size for multiple linear regression this study returned a minimum n = 107 (see Appendix A). For, *t* test, parameters included the following: the effect size (0.5), alpha (0.05), and power (0.95). The calculated sample size was 176 (see

Appendix B). Therefore, considering an additional 15% to account for attrition and missing data, the minimum sample size for this study was 202.

Instrumentation and Operationalization of Constructs

In this study, data were drawn from secondary data sources; therefore, I did not need a data collection instrument. Data were obtained from the CMS website (https://data.cms.gov/provider-data/dataset/fp6g-2gsn). The data were obtained from the highlighted source because the dataset contains information regarding 30-day readmissions across different hospitals (urban and rural). The source was also used because it is publicly accessible; therefore, I did not need to obtain site authorization or pay any additional fee. The source was also preferred because it is updated regularly with the recent update being July 28, 2022.

Operationalization

As earlier noted, this study includes three types of variables: one independent variable, one dependent variable and two covariables. In this section, the operational definition of each of the variables is provided including how it is measured or manipulated. The study includes only one independent variable, which is the hospital location. In this study, hospital location is defined based on whether the hospital serve urban population or the rural population. Therefore, in this study, the hospitals were grouped into two types: rural long-term care hospitals and urban long-term care hospitals. Based on the operational definition, the independent variable, hospital location, is a categorical variable that is measured on the dichotomous scale with two options urban or rural. The defined independent variable was calculated based on frequencies, which yielded the number of hospitals in each group.

The study included only one dependent variable, which is the 30-day readmission. In this study, the 30-day readmission refers to the unplanned readmissions occurring within 30 days after discharge (Kocakulah et al, 2021; Rubin et al., 2017). The 30-day readmission rates presented in the database consist of three types. One of the categories is the overall 30-day readmission, which refers to the rates of admission, 30 days after discharge from the hospital (hospital-wide). The second category is the 30-day readmission based on condition. The conditions that are considered include chronic obstructive pulmonary disease, heart attack, heart failure, and pneumonia. The third category is the 30-day readmission based on procedure. The procedures that are considered include CABG, and hip/knee replacement. In this study, the 30-day readmission was measured on a continuous scale and expressed as rates. I determined the number of 30-day readmissions in the urban and rural hospital for the three types described above and expressed the rates in percentages.

The covariate variables considered in this study included gender and primary payer status. Gender is expressed as a categorical variable measured on nominal scale and consisting of two options male or female. In this study, primary payer status is defined as the healthcare policy cover and grouped into three categories: Medicare and Medicaid, uninsured, and private insurance. Therefore, the covariate primary payer status was expressed as a categorical variable measured on a nominal scale.

Table 1

Summary of the Operationalization of the Variables

Variable	Type of variable	Definition	Measurement and expression
Hospital location	IV	Refers to whether the hospital serve urban population or the rural population	Categorical variable that is measured on the dichotomous scale with two options urban or rural
30-day readmission	DV	The unplanned readmissions occurring within 30 days including the overall 30-day readmission, readmission based on condition, and readmission based on procedure	Measured on a continuous scale and expressed as rates
Gender	CV	Refers to either of the two sexes (male and female)	Measured on nominal scale and consisting of two options male or female
Primary payer status	CV	Healthcare policy cover and grouped into three categories: Medicare and Medicaid, uninsured, or private insurance	Measured on nominal scale and consisting of three options Medicare and Medicaid, uninsured, or private insurance.

Note. IV = independent variable; DV = dependent variable; CV = covariate variable.

Data Analysis Plan

This section provides detailed description of the approaches that were used in the analysis of data to answer the study's research question. This study was guided by the following research question and respective hypothesis:

RQ: Using 2019 annual data, is there a significant difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

H_0: There is no statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

H_1: There is a statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

I used SPSS (Version 26) in the analysis of the retrieved data. Before the analysis of data, I first screened and cleaned the data. The first step was the filtering of the data based upon the state. Data were selected if the state was Tennessee. The selection was carried out using the SPSS select cases option, where the data were selected if "State = TN." The data were also sorted based on the hospital location. Data on the hospital location were assigned a numerical value to replace the alphabetical letter codes to facilitate the manipulation of data in SPSS. Rural hospitals were assigned code "0" while Urban hospitals were assigned code "1". The raw data on the type of 30-day readmission will also be number coded where 1= overall 30-day readmission, 0 = no readmission after 30 days. For the 30-day readmission based on condition, the coding was as follows: 1 = 30-day readmission due to chronic obstructive pulmonary disease, 2 = 30-day readmission due to heart attack, 3 = 30-day readmission due to heart failure, and 4 = 30-day readmission due to pneumonia. The data on the 30-day readmission based on procedure were coded as follows: 1 = 30-day readmission due to CABG, and 2 = 30-day readmission due to hip/knee replacement. The data relating to gender were assigned a numerical value to replace the alphabetical letter codes. Male was assigned a value of 0 while female was assigned a value of 1. The data relating to primary payer status was assigned numerical values as follows: “uninsured” was assigned value of 0 private insurance will be assigned a value of 1 and Medicare and Medicaid was assigned the value of 2.

The next step was to compile the data. The data were compiled to identify missing data and remove outliers. I obtained the descriptive statistics and frequencies from SPSS using crosstabulation to assess the summary of data of the variables of the study. From the summaries, I was able to identify if there were any missing values. The outliers were identified using boxplots.

After the cleaning of the data, descriptive statistics such as means, and standard deviation were used to describe the 30-day readmission rates between the urban and rural hospitals. Percentages were then used to describe the proportion of males and females and the proportion of the individuals with various primary payer status. Minimum and maximum values were used to determine the range and describe the data spread. Descriptive statistics were summarized using tables.

The difference in the 30-day readmission rates between the urban hospital and rural hospital were assessed using independent sample t-test. Assessment of the data to determine suitability of independent sample t-test was based on examination of whether various assumptions are met. The dependent variable (30-day readmission rate) was assessed to determine whether it meets the need to be measured at continuous level. Secondly, independent variable (hospital location) was assessed to determine whether it meets the need to consists of two categorical, independent groups. The data were assessed to determine whether there is no relationship between the observations in each group of the independent variable or between the groups themselves. Boxplots were used to determine whether the data meets the need for no significant outliers. Shapiro-Wilk test for normality was used to determine whether the data on 30-day readmission rate meets the need for approximately normally distributed for urban and rural hospital. Levene's test of equality of variances was used to determine whether the data meets the need for similarity in the population variance for each group of the independent variable (urban and rural hospital). The analysis was carried at 0.05 level of significance.

I conducted multiple linear regression to assess whether being elderly from rural long-term care hospitals predicted the likelihood of being readmitted 30 days after discharge. I assessed and controlled for the effect of gender and primary payer status (Medicare and Medicaid, uninsured, or private insurance) on the 30-day readmissions. Data were assessed to demonstrate the suitability of multiple linear regression the addressing the research question. First, the dependent variable, 30-day readmission rate, was measured at continuous level. The other assumption is that the independent variable, hospital location, is measured on a nominal scale, which was determined through the observation of whether the scale does or does not have intrinsic order. Those that do not have intrinsic order are nominal. In this study the hospital location had two categories that include urban and rural. The other variables gender and primary payer status were also measured on a nominal scale. The variable gender had two categories that include male and female. The other variable primary payer status had three categories that included Medicare and Medicaid, uninsured, or private insurance. The third assumption was the need for the presence of the independence of observations, which was determined by assessing the number of times a participant is counted in a sample. The sample where each participant is counted once have independence of observation. The independence of observations was also checked using the SPSS Statistics' Durbin-Watson statistics. The Durbin-Watson statistic can range from 0 to 4 but a value of approximately 2 indicates that there is no correlation between residuals, hence independence of residuals (Laerd Statistics, 2017). The fourth assumption was the need for a (a) linear relationship between the dependent variable and each of the independent variables, which was assessed using partial regression plots between each independent variable and the dependent variable (excluding the categorical variables gender and primary payer status). (b) linear relationship between the dependent variable and the independent variables collectively, which was assessed using a scatterplot of the studentized residuals against the (unstandardized) predicted values. The fifth assumption was the presence of no multicollinearity. Test for multicollinearity was carried out using the variance inflation factor (VIF). The VIF above 5 indicates the presence of multicollinearity, therefore the assumption is not met (Ramanathan, 2010; Leinonen et al., 2012). The sixth assumption was presence of no significant outliers. The outliers were checked using case wise diagnostics (Laerd Statistics, 2017). The assumption regarding outliers was considered to have been met if 99% of the dataset fell within + or – 3 standard deviations from the mean. If assumptions was not be met, I checked for outliers and if any exist, filtered out the outliers before running the regression analysis again, or alternately, transform the data (Laerd Statistics, 2015). The seventh assumption was the need for the residuals (errors) to be approximately normally distributed, which was assessed using normal Q-Q Plot of the studentized residuals. The analysis was carried out at 0.05 level of significance.

Threats to Validity

Given that the study was based on secondary data already, the description of validity focuses on how the data were collected and validated. The data used in the study were collected from Medicare enrollment and claims data and Veterans Health Administration administrative data and published by the CMS. The three bodies have standardized approaches to data collection that ensure generalizability, therefore the data meets the external validity requirement. However, there are concerns of accuracy in data documentation caused by possible variation in approaches used by the different data entry personnel across the different data entry points. To address the highlighted concern, the research assessed the data to determine if data vary greatly from each another by checking for outliers.

Ethical Procedures

Since the study involves the use of secondary data, few ethical issues are expected. For example, I was not required to obtain consent from the participants because the data have already been collected by CMS and the data files are publicly available. I was also not required to obtain site authorization because of the data are free to access by the public. Despite being fewer ethical issues, the study still adhered to the ethical requirements as documented in the Belmont report and the University Institutional Review Board (IRB) requirements.

According to Walden University IRB, it is mandatory for post graduate researchers to obtain the board's approval before proceeding with the data collection. I obtained approval from the University's IRB (IRB number - 06-13-23-0112857) and strictly adhered to the Board's regulations. To obtain the approval, I presented the research protocol, the instrumentation, and approach that were used in the analysis as requested by the board. Data collection only commenced after the IRB approval was obtained. After obtaining the IRB approval, I made no alteration to the research protocol or other aspect of the research.

As noted by Campbell and Cecil (1979), the *Belmont Report* requires health science researchers carrying out statistical analysis of secondary data including administrative records need to pay attention to the rules and regulations outlined by the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research. The regulations require researchers to adhere to three main ethical principles that include respect, justice, and beneficence. The Belmont report identifies the respect for persons as one of the important ethical considerations that research based on secondary data should uphold (U.S. Department of Health, Education, and Welfare, 2014). According to Miracle (2016), there are various ways in which researchers can uphold the principles of respect for persons with one of the ways being ensuring the adherence to anonymity rule. Friesen et al. (2017) also noted that researchers can adhere to the principle of respect for persons by administering informed consent that enables the participants to understand the study, risks and benefits and the nature of their participation before agreeing to take part. However, as stated in the Belmont report, research that involves statistical analysis for secondary data including administrative records poses no risk to the participants (Campbell & Cecil, 1979). However, Belmont report exclusively indicates that secondary data analysis does not cause risks to the participants if the data being used contains no individually identifiable information (Campbell & Cecil, 1979). Therefore, the Belmont report requires that secondary data analysis upholds anonymity by ensuring that the dataset do not contain information that can be used to link the data to the participants. Some of the information that can be used to link the data to the participants include the name, phone number, physical address, job ID, PIN, and other contact information. It should be noted that the data that were used in this research do not contain individually identifiable information. Additionally, I assessed the data to confirm that no individually identifiable information is present in the downloaded data. Any information that was deemed to expose the identity of the participants from the downloaded dataset was deleted before the data is processed. It should be noted that by checking for the possible presence and subsequent deletion of the individually identifiable data before data processing, I was able to protect the primary respondents from potential risks and harm (Miracle, 2016).

The Belmont report also identifies the principle of justice as the other important ethical considerations that research based on secondary data should uphold (U.S. Department of Health, Education, and Welfare, 2014). One way in which research based on secondary analysis of data can be uphold the principle of justice is by ensuring the participants' right to access the study findings. As already indicated, I did not issue an informed consent and therefore did not commit to the participants to share the findings of the study. However, Belmont report requires researchers who use publicly available data to also ensure that at least the summary of the findings is made available to the public (Miracle, 2016). There are various ways in which researchers can ensure that the outcome from secondary data analysis is made publicly available. Some of the approaches include providing summary of the findings in public libraries or publishing the manuscripts in online databases. In this research, the manuscript was published in the free to access online database.

Honesty is an important ethical principle when you are dealing with secondary data. It is important for researchers to ensure that approaches used in data processing, analysis and presentation adhere to honest reporting. In this study, I ensured honest reporting by upholding data fidelity and avoiding any erroneous and malicious manipulation of data. Erroneous manipulation of data was limited using appropriate statistical tests that led me to obtain factual findings emerging from the data.

Data protection is an important ethical practice among researchers, which calls for secure storage and restricted access by third parties (U.S. Department of Health, Education, and Welfare, 2014). I ensured that the data were safely stored, and I alone accessed it. The steps taken to securely store the data included the use of an encrypted laptop. Additionally, I independently completed the data processing steps including de-identification processes, coding, and actual analysis. Further, I maintained the data for three years following research study completion after which the data will be destroyed by permanently deleting it from the laptop.

Summary

This section described in detail the design and methodology of the method of inquiry. The quantitative methodology based on descriptive design is identified as suitable in addressing the study's research question. The section also identified patients in urban and the rural long-term care hospitals in Tennessee whose readmission data have been documented in the CMS database as the target population. Using a well-described selection criteria, the study considered a minimum sample size of 202. The section also provides a detailed account of operationalization of the study variables. The independent sample *t* test and multiple linear regression are described as the suitable statistical tests for determining the difference in the 30-day readmission rates between the urban hospital and rural hospital. The implementation of the methodological steps presented in Section 2 will yield findings that will be described in Section 3.

Section 3: Presentation of the Results and Findings

Introduction

The purpose of this quantitative descriptive study was to determine whether differences in 30-day readmission rates among the elderly exist between urban and rural long-term care hospitals in Tennessee. The study addressed the following research question and the associated hypotheses:

RQ: Using 2019 annual data, is there a significant difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

H_0: There is no statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

H_1: There is a statistically significant using 2019 annual data, difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge?

In this section, the findings obtained from the analysis of secondary data obtained from the CMS website are presented. First, the description of the data collection approaches is provided. Secondly, the results including the descriptive statistics and the outcome of the hypothesis testing are described. Finally, the summary of Section 3 is provided along with transitional material.

Data Collection of Secondary Data Set

Initially, I planned to collect only 2019 annual data on potentially preventable hospital readmissions 30 days after discharge. Relying on the 2019 annual data, I sought to obtain the calculated sample size of 202. However, upon downloading and sorting out the 2019 annual data, which included quarterly data (March 2019, June 2019, September 2019, and December 2019), it was noted that the eligible data (*n* = 32) were less than required sample. Therefore, instead of considering the 2019 annual data only, I sampled data available on the database (2016-2022).

The data used in this study was obtained from the CMS website. However, there were slight variations in the steps followed in the collection of data from the steps previously described in the methodology. The steps followed in extracting data from the different yearly data sets are described using the example of 2019 annual data.

The initial step in the collection of data from the 2019 annual dataset involved downloading the entire dataset which contained a total of 99,531 data units from different states across the United States. The data also contained information from different long-term care hospitals in different states across the United States. The second step, therefore, involved the selection of data from long-term hospitals in the state of Tennessee. By excluding other states, the data were reduced to 2088.

The third step involved the selection of data based on the measures. The 2019 annual dataset has different measures included Catheter-associated urinary tract infections (L_006_01), Central line-associated bloodstream infections (L_007_01), Percentage of patients whose activities of daily living and thinking skills were assessed and related goals were included in their treatment plan (L_009_02); Percentage of patients whose functional abilities were assessed and functional goals were included in their treatment plan (L_010_02); Change in ability to move around for patients admitted on a ventilator (L_011_04); Percentage of LTCH patients who experience one or more falls with major injury during their LTCH stay (L_012_01); Clostridium difficile infection (L_014_01); Influenza vaccination coverage among healthcare personnel (L_015_01); Rate of potentially preventable hospital readmissions 30 days after discharge from an LTCH (L_017_01); Rate of successful return to home or community from an LTCH (L_018_02); Medicare Spending Per Beneficiary (MSPB) for patients in LTCHs (L_019_01); Percentage of patients whose medications were reviewed and who received follow-up care when medication issues were identified (L_020_01); Percentage of patients with pressure ulcers/pressure injuries that are new or worsened (L_021_01); Spontaneous Breathing Trials – Percentage of patients on ventilators assessed for readiness to begin breathing trials without a ventilator within the first 2 days of their LTCH stay (component 1), and the percentage of patients on ventilators who appropriately received breathing trials within the first 2 days of their LTCH stay (component 2) (L_022_01)). The measure 'Rate of potentially preventable hospital readmissions 30 days after discharge from an LTCH (L_017_01)' was selected resulting in the reduction of the dataset to 177.

The fourth step involved the selection of the appropriate rate of potentially preventable hospital readmissions 30 days after discharge from an LTCH (L_017_01) measure code. From the described L_017_01 measure codes, L_017_01_PPR_PD__RSRR with 32 data units and L_017_01_PPR_PD_OBS_READM with 16 data units were selected and used in this study.

There were some differences in the L_017_01 measure code reported across the different annual data sets. For example, the 2016, 2017 and 2018 annual datasets did not report the Number of Potentially Preventable Readmissions Following Discharge but reported the Risk-Standardized Potentially Preventable Readmission Rate. The 2020, 2021 and 2022 reported both the Risk-Standardized Potentially Preventable Readmission Rate and the Number of Potentially Preventable Readmissions. It should also be noted that the number of times the data were collected per year across different annual datasets varied as follows: the 2016 dataset only included the data collected in the December of that year; the 2017, 2018, 2019 and 2022 datasets included the data collected four times (quarterly); the data for 2020 were collected three times in that year; and the 2021 dataset only contained September and December data. A summary of the data units for each measure code per year is provided in Table 2. Note that the data for 2018 is not presented in Table 2 because the score was marked as “Not available score” and therefore excluded.

Table 2

Summary of the Selected Annual Data

Year	Risk-standardized potentially preventable readmission rate	No. of potentially preventable readmissions	Unadjusted potentially preventable readmission rate	Comparative performance category	No. of eligible stays
2016	9	-	-	9	10
2017	33	-	-	33	36
2018	-	-	-	-	-
2019	32	16	16	16	16
2020	24	24	41	24	24
2021	15	15	15	15	15
2022	28	28	28	28	28

After the extraction and selection of the required data, I classified the data into two groups (urban and rural). It should be noted that the datasets contained the different regions across the counties in Tennessee from which the data were collected. I relied on the definition of urban areas provided by the Tennessee Department of Health (https://www.tn.gov/health/cedep/environmental/healthy-places/healthy-places/land-use/lu/urban-areas.html) to classify the data as either urban or rural. According to the definition, urban areas are those with a population of greater than 50,000. The classification resulted in the data from two areas (Bristol, in Sullivan County, and Powell, Knox County) being classified as rural, and data from four areas being classified as urban: Chattanooga (Hamilton County), Knoxville (Knox County), Memphis (Shelby County), and Nashville (Davidson County).

Results

Number of Eligible Stays

The mean number of eligible stays varied across the different years. As shown in Table 3, the highest mean number of eligible stays was recorded in 2016 (*M* = 308.5, *SD* = 121.560, *n* = 10). Table 3 also shows the lowest mean number of eligible stays was recorded in 2022 (M = 163.2, *SD* = 95.318, *n* = 28).

Table 3

Mean Number of Eligible Stays Across the Different Years

Year	*M*	*n*	*SD*
2016	308.5	10	121.560
2017	285.6	36	100.819
2019	223.1	16	82.414
2020	233.8	24	94.832
2021	265.7	15	110.769
2022	163.2	28	95.318
Total	241.1	129	108.850

The mean number of eligible stays also varied across the different counties. As shown in Table 4, the long-term care hospitals (*n* = 21) in Knox County had the highest mean score (*M* = 331.7, *SD* = 77.439) for the number of eligible stays. The long-term care hospitals (*n* = 27) in Davidson County had a mean number of eligible stays of 272.5 (*SD* = 113.016). The long-term care hospitals (*n* = 16) in Sullivan County had a mean number of eligible stays of 243.6 (*SD* = 90.052). The long-term care hospitals (*n* = 16) in Hamilton County had a mean number of eligible stays of 207.1 (*SD* = 69.719). Table 4 also shows that the long-term care hospitals (*n* = 49) in Shelby County had the lowest mean number of eligible stays (*M* = 195.2, *SD* = 106.987).

Table 4

Mean Number of Eligible Stays Across the Different Counties

County name	*M*	*n*	*SD*
Davidson	272.5	27	113.016
Hamilton	207.1	16	69.719
Knox	331.7	21	77.439
Shelby	195.2	49	106.987
Sullivan	243.6	16	90.052
Total	241.1	129	108.850

Table 5 shows the mean number of eligible stays for the rural and urban long-term care hospitals. It is evident from Table 5 that the rural long-term care hospitals (n = 32) had the highest mean score (M = 287.9, SD = 98.996) for the number of eligible stays. Table 5 also indicates that the urban long-term care hospitals (n = 97) had the lowest mean score (M = 225.6, SD = 107.989) for the eligible stays.

Table 5

Mean Number of Eligible Stays for the Rural and Urban Long-Term Care Hospitals

Status	*M*	*n*	*SD*
Rural	287.9	32	98.996
Urban	225.6	97	107.989
Total	241.1	129	108.850

An independent-samples t test was run to determine if there were differences in the number of eligible stays between urban and rural long term care hospitals. The findings presented in Table 6 indicate presence of statistically significant difference. Therefore, the number of eligible stays in the urban long-term care hospitals (M = 225.6, *SD* = 107.989) was statistically significantly lower than the mean number of eligible stays (*M* = 287.9, *SD* = 98.996) in rural long term care hospitals, $t(127) = 2.885$, $p = .005$.

Table 6

Independent-Samples T-Test Showing Differences in the Number of Eligible Stays Between Urban and Rural Long Term Care Hospitals

				95% Confidence interval of the difference	
F	*t*	*df*	Sig.	Lower	Upper
2.951	2.885	127	0.005	19.550	104.963

A two-way analysis of variance (ANOVA) was conducted to examine the effects of year and rurality status on the number of eligible stays (see Table 7). There was no statistically significant interaction between year and rurality status on the number of eligible stays, $F(5, 117) = 0.455$, $p = .809$, partial η2 = .019 (see Table 7). As shown in Figure 1, the number of eligible stays were high in rural long-term care hospitals compared to urban long-term care hospitals across all the years.

Table 7

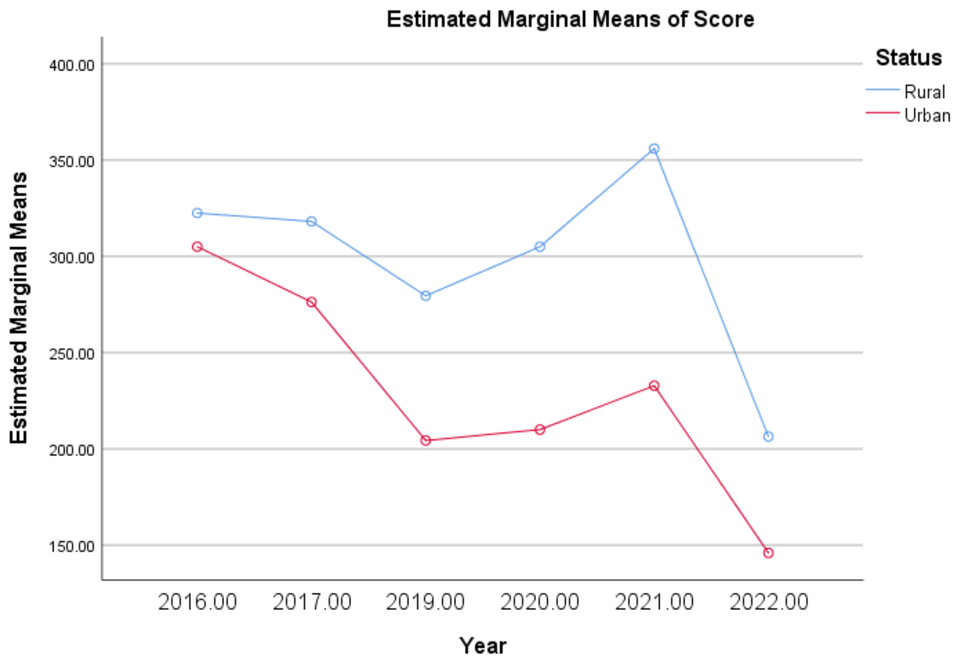
Two-Way ANOVA Showing the Effects of Year and Rurality Status on the Number of Eligible Stays

Source	Type III *SS*	*df*	*MS*	*F*	*Sig.*	Partial η2
Corrected model	436353.666 [a]	11	39668.515	4.296	0	0.288
Intercept	5383181.28	1	5383181.28	583.049	0	0.833
Year	228872.305	5	45774.461	4.958	0	0.175
Status	91893.225	1	91893.225	9.953	0.002	0.078
Year * status	21019.831	5	4203.966	0.455	0.809	0.019
Error	1080239.22	117	9232.814			
Total	9014827	129				
Corrected total	1516592.88	128				

[a] $R^2 = .288$ (Adjusted $R^2 = .221$).

Figure 1

Number of Eligible Stays in Rural and Urban Long-Term Care Hospitals Between 2016 and 2022



Potentially Preventable Readmissions Following Discharge

The mean potentially preventable readmissions following discharge score varied across the different years. As shown in Table 8, the highest mean number of potentially preventable readmissions following discharge score was recorded in 2021 (M = 41.5, SD = 19.497, n = 15). In 2019 (n = 16), the mean number of potentially preventable readmissions following discharge score was 29.1 (SD = 13.401). In 2020 (n = 24), the mean number of potentially preventable readmissions following discharge score was 32.6 (SD = 16.615). Table 8 also shows the lowest mean number of potentially preventable readmissions following discharge score was recorded in 2022 (*M* = 24.7, *SD* = 15.318, *n* = 28).

Table 8

Mean Number of Potentially Preventable Readmissions Following Discharge Score Across the Different Years.

Year	*M*	*n*	*SD*
2019	29.1	16	13.401
2020	32.6	24	16.615
2021	41.5	15	19.497
2022	24.7	28	15.318
Total	30.9	83	16.954

The mean number of potentially preventable readmissions following discharge score also varied across the different counties. As shown in Table 9, the long-term care hospitals (*n* = 11) in Knox County had the highest mean score (*M* = 51.7, *SD* = 19.875) for the number of potentially preventable readmissions following discharge. The long-term care hospitals (*n* = 17) in Davidson County had a mean number of potentially preventable readmissions following discharge score of 32.1 (*SD* = 16.101). The long-term care hospitals (*n* = 11) in Sullivan County had a mean number of potentially preventable readmissions following discharge score of 30.2 (*SD* = 9.119. The long-term care hospitals (*n* = 33) in Shelby County had a mean number of potentially preventable readmissions following discharge score of 26.8 (*SD* = 15.415. Table 9 also shows that the long-term care hospitals (*n* = 11) in Hamilton County had the lowest mean number of potentially preventable readmissions following discharge score (*M* = 21.2, *SD* = 7.922).

Table 9

Mean Potentially Preventable Readmissions Following Discharge Score Across the Different Counties

County name	*M*	*n*	*SD*
Davidson	32.1	17	16.101
Hamilton	21.2	11	7.922
Knox	51.7	11	19.875
Shelby	26.8	33	15.415
Sullivan	30.2	11	9.119
Total	30.9	83	16.954

Table 10 shows the mean number of potentially preventable readmissions following discharge in the rural and urban long-term care hospitals. It is evident from Table 10 that the rural long-term care hospitals (*n* = 22) had the highest mean score (*M* = 41.0, *SD* = 18.689) for the number of potentially preventable readmissions following discharge. Table 10 also indicates that the urban long-term care hospitals (*n* = 61) had the lowest mean score (*M* = 27.2, *SD* = 14.830) for the number of potentially preventable readmissions following discharge.

Table 10

Mean Potentially Preventable Readmissions Following Discharge Score in the Rural and Urban Long-Term Care Hospitals

Status	*M*	*n*	*SD*
Rural	41.0	22	18.689
Urban	27.2	61	14.830
Total	30.9	83	16.954

An independent-samples t-test was run to determine if there were differences in the number of potentially preventable readmissions following discharge between urban and rural long term care hospitals. The findings presented in Table 11 indicate presence of statistically significant difference. Therefore, the number of potentially preventable readmissions following discharge in the urban long term care hospitals (27.2 ± 14.830) was statistically significantly lower than the mean number of potentially preventable readmissions (41.0 ± 18.689) in rural long term care hospitals (t (81) = 3.462, p = 0.001).

Table 11

Independent-Samples T-Test Showing Differences in the Number of Potentially Preventable Readmissions Following Discharge Between Urban and Rural Long-Term Care Hospitals

					95% confidence interval of the difference	
	F	*t*	*df*	p-value	Lower	Upper
Equal variances assumed	0.305	3.462	81	0.001	5.831	21.586

A two-way ANOVA was conducted to examine the effects of year and rurality status on the number of potentially preventable readmissions following discharge (see Table 12). Data mean ± standard deviation, unless otherwise stated. There was no statistically significant interaction between year and rurality status on the number of potentially preventable readmissions following discharge, $F(3, 75) = 0.328$, $p = .0805$, partial $\eta 2 = .013$ (see Table 12). As shown in Figure 2, the number of potentially preventable readmissions following discharge were high in rural long term care hospitals compared to urban long term care hospitals across all the year groups.

Table 12

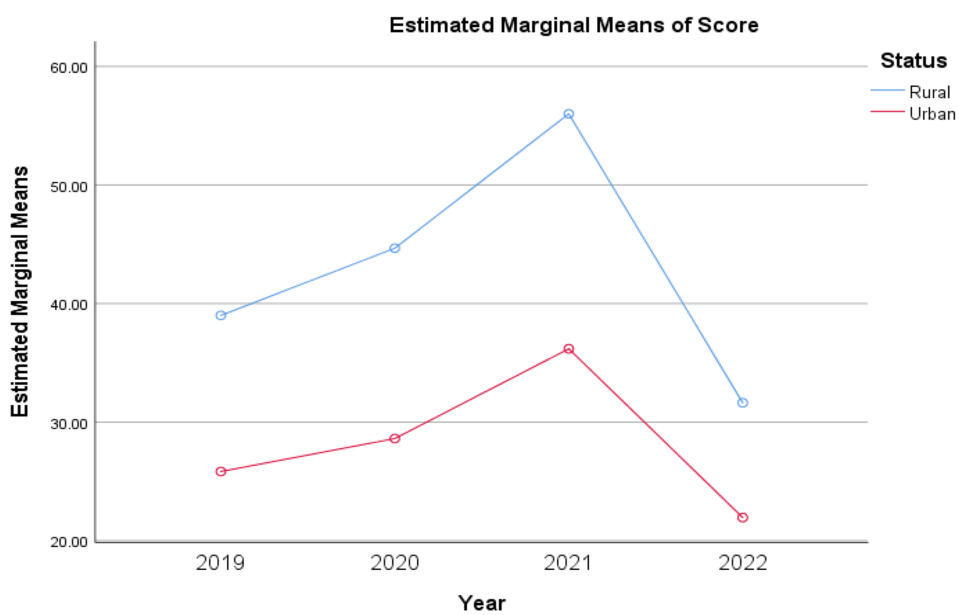
Two-Way ANOVA Showing Effects of Year and Rurality Status on the Potentially Preventable Readmissions Following Discharge

Source	Type III *SS*	*df*	*MS*	*F*	Sig.	Partial η2
Corrected model	6235.056 [a]	7	890.722	3.854	0.001	0.265
Intercept	75206.402	1	75206.402	325.405	0	0.813
Year	3059.29	3	1019.763	4.412	0.007	0.15
Status	3217.557	1	3217.557	13.922	0	0.157
Year * status	227.234	3	75.745	0.328	0.805	0.013
Error	17333.739	75	231.117			
Total	102713	83				
Corrected total	23568.795	82				

[a] R^2= .265 (Adjusted R^2 = .196).

Figure 2

Potentially Preventable Readmissions Following Discharge in Rural and Urban Long Term Care Hospitals Between 2016 and 2022



Comparative Performance Category

The comparative performance category provided information on how potentially preventable 30-day readmission rates in the assessed long-term care hospitals were compared to the national preventable 30-day readmission rates. In each county, the number of long-term care hospitals that performed better or worse than the national rate in terms of potentially preventable 30-day readmission rates were recorded. As shown in Table 13, in Davidson County with a total of 27 long-term care hospitals that were assessed, 63% (n = 17) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 22% (n = 6) of them had potentially preventable 30-day readmission rates that were better than the national rate and 14.8% (n = 4) of them had potentially preventable 30-day readmission rates that were worse than the national rate.

In Hamilton County with a total of 16 long-term care hospitals that were assessed, 68.8% (n = 11) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 31.3% (n = 5) of them had potentially preventable 30-day readmission rates that were better than the national rate and no hospital with potentially preventable 30-day readmission rates that were worse than the national rate (Table 13). In Knox County with a total of 21 long-term care hospitals that were assessed, 52.4% (n = 11) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 28.6% (n = 6) of them had potentially preventable 30-day readmission rates that were better than the national rate and 19% (n = 4) of them had potentially preventable 30-day readmission rates that were worse than the national rate. In Shelby County with a total of 45 long-term care hospitals that were assessed, 84.4% (*n* = 15) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 11.1% (*n* = 5) of them had potentially preventable 30-day readmission rates that were better than the national rate and 14.4% (*n* = 2) of them had potentially preventable 30-day readmission rates that were worse than the national rate. In Sullivan County with a total of 16 long-term care hospitals that were assessed, 93.8% (*n* = 15) of them had potentially preventable 30-day readmission rates that were not different than the national rate, only 6.3% (*n* = 1) of them had potentially preventable 30-day readmission rates that were better than the national rate and no hospital had potentially preventable 30-day readmission rates that were worse than the national rate (Table 13).

Table 13

Comparative Performance of the Long-Term Care Hospitals Across the Different Counties

County		Better than the national rate	No different than national rate	Worse than the national rate	Total
Davidson	*n*	6	17	4	27
	%	22.2%	63.0%	14.8%	100%
Hamilton	*n*	5	11	0	16
	%	31.3%	68.8%	0.0%	100%
Knox	*n*	6	11	4	21
	%	28.6%	52.4%	19.0%	100%
Shelby	*n*	5	38	2	45
	%	11.1%	84.4%	4.4%	100%
Sullivan	*n*	1	15	0	16
	%	6.3%	93.8%	0.0%	100%
Total	*n*	23	92	10	125
	%	18.4%	73.6%	8.0%	100%

Chi-square test of homogeneity was carried out to assess the differences between the reported proportions of the comparative performance categories across the different counties. The findings indicate that the reported differences in the proportion of better, no different, and worse than the national rate categories statistically significantly differed across the different counties ($\chi 2(8) = 16.809$, $p = 0.032$). The Chi-square test of homogeneity findings are presented in Table 14.

Table 14

Chi-Square Test of Homogeneity Showing Differences Between the Reported Proportions of the Comparative Performance Categories Across the Different Counties

	Value	*df*	Asymptotic Significance (2-sided)
Pearson chi-square	16.809 [a]	8	0.032
Likelihood ratio	18.573	8	0.017
N of valid cases	125		

[a] 9 cells (60.%) have expected count less than 5. The minimum expected count is 1.28.

Table 15 shows the number of long-term care hospitals that performed better or worse than the national rate in terms of potentially preventable 30-day readmission rates between 2016 and 2022. In 2016 where a total of 9 long-term care hospitals that were assessed, 22.2% ($n = 2$) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 44.4% ($n = 4$) of them had potentially preventable 30-day readmission rates that were better than the national rate and 33.4% ($n = 3$) of them had potentially preventable 30-day readmission rates that were worse than the national rate. In 2017 where a total of 33 long-term care hospitals that were assessed, 21.2% ($n = 7$) of them had potentially preventable 30-day readmission rates that were not different than the national rate, 57.6% ($n = 19$) of them had potentially preventable 30-

day readmission rates that were better than the national rate and 21.2% (*n* = 7) of them had potentially preventable 30-day readmission rates that were worse than the national rate (Table 15). In 2019 where a total of 16 long-term care hospitals were assessed, all hospitals had potentially preventable 30-day readmission rates that were better than the national rates. Similarly, all the assessed hospitals in 2020 (n = 24, 100%), 2021 (n = 15, 100%), and 2022 (n = 28, 100%) had potentially preventable 30-day readmission rates that were better than the national rates (Table 15).

Table 15

Comparative Performance of the Long-Term Care Hospitals Across the Different Years

Year		Better	No Different	Worse	Total
2016	%	4	2	3	9
	n	44.4%	22.2%	33.3%	100%
2017	%	19	7	7	33
	n	57.6%	21.2%	21.2%	100%
2019	%	0	16	0	16
	n	0.0%	100%	0.0%	100%
2020	%	0	24	0	24
	n	0.0%	100%	0.0%	100%
2021	%	0	15	0	15
	n	0.0%	100%	0.0%	100%
2022	%	0	28	0	28
	n	0.0%	100%	0.0%	100%
Total	%	23	92	10	125
	n	18.4%	73.6%	8.0%	100%

Chi-square test of homogeneity was carried out to assess the differences between the reported proportions of the comparative performance categories across the different years. The findings indicate that the reported differences in the proportion of better, no different, and worse than the national rate categories statistically significantly differed across the different years ($\chi 2(10) = 90.569$, $p = 0.001$). The Chi-square test of homogeneity findings are presented in Table 16.

Table 16

Chi-Square Test of Homogeneity Showing Differences Between the Reported Proportions of the Comparative Performance Categories Across the Different Years

	Value	*df*	Asymptotic Significance (2-sided)
Pearson Chi-Square	90.569 [a]	10	0.000
Likelihood Ratio	101.294	10	0.000
N of Valid Cases	125		

[a] 10 cells (55.6%) have expected count less than 5. The minimum expected count is .72.

The comparative performance of the long-term care hospitals in terms of potentially preventable 30-day readmission rates was also determined among those in rural and urban areas. Among the rural long-term care hospitals that were assessed (n = 32), 81.3% (n = 26) had potentially preventable 30-day readmission rates that were not different than the national rate, 18.8% (n = 6) had potentially preventable 30-day readmission rates that were better than the national rate and none had potentially preventable 30-day readmission rates that were worse than the national rate. Table 17 also shows that 71% (n = 66) of the urban long-term care hospitals that were assessed (n = 93) had potentially preventable 30-day readmission rates that were not different than the national rate. The findings also indicate that 18.3% (n = 17) of the urban long-term care hospitals had potentially preventable 30-day readmission rates that were better than the national rate while 10.8% (n = 10) had potentially preventable 30-day readmission rates that were worse than the national rate (Table 17).

Table 17

Comparative Performance of the Rural and Urban Long-Term Care Hospitals

Status		Better	No Different	Worse	Total
Rural	%	6	26	0	32
	n	18.8%	81.3%	0.0%	100%
Urban	%	17	66	10	93
	n	18.3%	71.0%	10.8%	100%
Total	%	23	92	10	125
	n	18.4%	73.6%	8.0%	100%

Chi-square test of homogeneity was carried out to assess the differences between the reported proportions of the comparative performance categories between rural and urban long term care hospitals. The findings indicate that the reported differences in the proportion of better, no different, and worse than the national rate categories statistically significantly differed between rural and urban long term care hospitals. ($\chi2(2) = 3.786$, $p = 0.151$). The Chi-square test of homogeneity findings are presented in Table 18.

Table 18

Chi-Square Test of Homogeneity Showing Differences Between the Reported Proportions of the Comparative Performance Categories in Rural and Urban Long-Term Care Hospitals

	Value	*df*	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.786 [a]	2	0.151
Likelihood Ratio	6.252	2	0.044
N of Valid Cases	125		

[a] 1 cells (16.7%) have expected count less than 5. The minimum expected count is 2.56.

Unadjusted Potentially Preventable Readmission Rate

The mean unadjusted potentially preventable readmission rates score also varied across the different years. As shown in Table 19, the highest mean unadjusted potentially preventable readmission rate score was recorded in 2021 (15.3 ± 1.699, *n* = 15) and 2022 (15.3 ± 2.588, *n* = 28). In 2020 (*n* = 24), the mean unadjusted potentially preventable readmission rate score was 13.6 ± 3.018. In 2019 (*n* = 16), the mean unadjusted potentially preventable readmission rate score was 12.9 ± 3.275 (Table 19).

Table 19

Mean Unadjusted Potentially Preventable Readmission Rates Score Across the Different Years

Year	Mean	*N*	Std. Deviation
2019	12.9	16	3.275
2020	13.6	24	3.018
2021	15.3	15	1.699
2022	15.3	28	2.588
Total	14.3	83	2.862

The data also provided scores for the unadjusted potentially preventable readmissions rates for the different counties. As shown in Table 20, the long-term care hospitals (*n* = 11) in Sullivan County had the highest mean score (15.7 ± 1.496) for the unadjusted potentially preventable readmissions. The long-term care hospitals (*n* = 17) in Davidson County had an unadjusted potentially preventable readmissions mean score of 14.0 ± 2.169. The long-term care hospitals (*n* = 11) in Knox County had an unadjusted potentially preventable readmissions mean score of 14.5 ± 1.286. The long-term care hospitals (*n* = 33) in Shelby County had an unadjusted potentially preventable readmissions mean score of 14.7 ± 3.681. Table 20 also shows that the long-term care hospitals (*n* = 11) in Hamilton County had the lowest mean score (12.3 ± 2.339) for the unadjusted potentially preventable readmissions.

Table 20

Mean Unadjusted Potentially Preventable Readmission Rates Score Across the Different Counties

County Name	Mean	*N*	Std. Deviation
Davidson	14.0	17	2.169
Hamilton	12.3	11	2.339
Knox	14.5	11	1.286
Shelby	14.7	33	3.681
Sullivan	15.7	11	1.496
Total	14.3	83	2.862

Table 21 shows the mean unadjusted potentially preventable readmission rates score for the rural and urban long-term care hospitals. It is evident from Table 21 that the urban long-term care hospitals (*n* = 61) had the lowest mean score (14.1 ± 3.185) for the unadjusted potentially preventable readmissions. Table 21 also indicates that the rural long-term care hospitals (*n* = 22) had the highest score (15.1 ± 1.479) for the unadjusted potentially preventable readmissions.

Table 21

Mean Unadjusted Potentially Preventable Readmission Rates Scores in Rural and Urban Long Term Care Hospitals

Status	Mean	*N*	Std. Deviation
Rural	15.1	22	1.479
Urban	14.1	61	3.185
Total	14.3	83	2.862

An independent-samples t-test was run to determine if there were differences in unadjusted potentially preventable readmission rates scores between urban and rural long term care hospitals. The findings presented in Table 22 indicate lack of statistical significance. Therefore, there was no statistically significant difference in the unadjusted potentially preventable readmission rates scores between rural (15.1 ± 1.479) and urban (14.1 ± 3.185) long term care hospitals ($t(139) = -0.343$, $p = 0.732$).

Table 22

Independent-Samples T-Test Showing Differences in Unadjusted Potentially Preventable Readmission Rates Scores Between Urban and Rural Long Term Care Hospitals

	F	*t*	*df*	*Sig*	95% Confidence Interval of the Difference	
					Lower	Upper
Equal variances assumed	14.205	1.451	81	0.151	-0.38109	2.432

A two-way ANOVA was conducted to examine the effects of year and rurality status on the unadjusted potentially preventable readmission rates scores (Table 23). Data mean ± standard deviation, unless otherwise stated. There was a statistically significant interaction between year and rurality status on the unadjusted potentially preventable readmission rates scores, F (3, 75) = 0.097, p = .0961, partial $\eta 2$ = .004. As shown in Figure 3, the unadjusted potentially preventable readmission rates scores were high in rural long term care hospitals compared to urban long term care hospitals across all the years.

Table 23

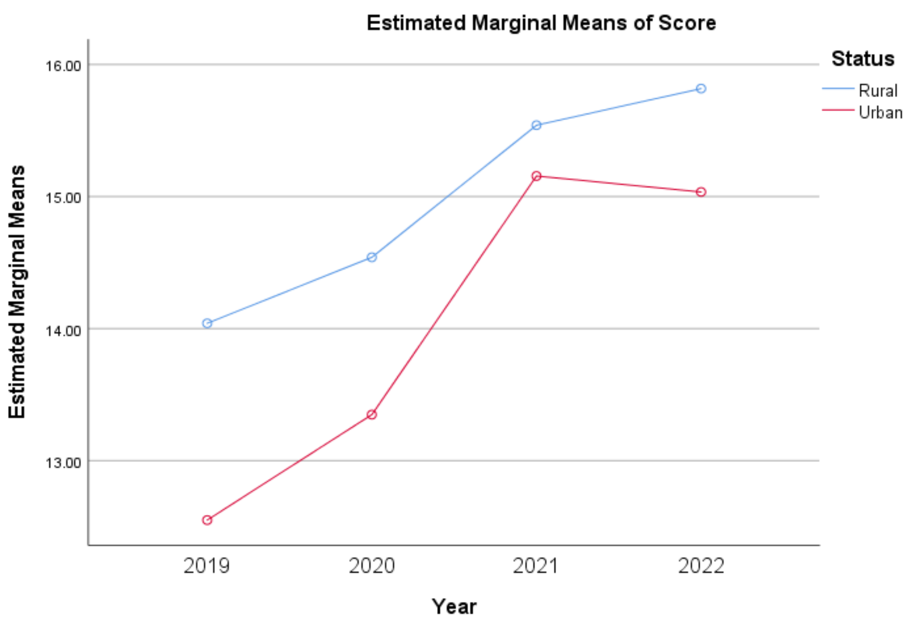
Two-Way ANOVA Showing the Effects of Year and Rurality Status on the Unadjusted Potentially Preventable Readmission Rates Scores

Source	Type III sum of squares	*df*	Mean square	*F*	*Sig.*	Partial Eta squared
Corrected Model	96.935a	7	13.848	1.808	0.098	0.144
Intercept	12564.095	1	12564.095	1640.087	0	0.956
Year	50.333	3	16.778	2.19	0.096	0.081
Status	13.828	1	13.828	1.805	0.183	0.024
Year * Status	2.234	3	0.745	0.097	0.961	0.004
Error	574.547	75	7.661			
Total	17743.54	83				
Corrected Total	671.483	82				

a. *R* Squared = .144 (Adjusted *R* Squared = .065)

Figure 3

Unadjusted Potentially Preventable Readmission Rates Scores in Rural and Urban Long Term Care Hospitals Between 2016 and 2022



Risk-Standardized Potentially Preventable Readmission Rate

The data provided scores for the risk-standardized potentially preventable readmissions rates for the different counties. The determination of the risk-standardized potentially preventable readmissions rate involved controlling for the various aspects including Age/sex categories; original reason for Medicare entitlement (age, disability or ESRD); surgery category if present (e.g., cardiothoracic, orthopedic), receiving dialysis in prior short-term stay, defined by the presence of revenue code; principal diagnosis on the prior short-term claim; comorbidities from secondary diagnoses on the prior short-term claim and diagnoses from earlier short-term stays up to one year before PAC admission (these are clustered using the Hierarchical Condition Categories [HCC] groups used by CMS); length of stay in the prior short-term hospital stay (categorical to account for nonlinearity); prior acute ICU/CCU utilization (days) (categorical); and the count of prior short-term discharges in the prior year (CMS, 2015). As shown in Table 24, the long-term care hospitals (n = 23) in Knox County had the highest mean score (18.2 ± 4.754) for the risk-standardized potentially preventable readmissions. The long-term care hospitals (n = 31) in Davidson County had a risk-standardized potentially preventable readmissions mean score of 17.2 ± 5.739. The long-term care hospitals (n = 18) in Sullivan County had a risk-standardized potentially preventable readmissions mean score of 17.2 ± 4.628. The long-term care hospitals (n = 51) in Shelby County had a risk-standardized potentially preventable readmissions mean score of 16.7 ± 4.817. Table 24 also shows that the long-term care hospitals (n = 18) in Hamilton County had the lowest mean score (16.2 ± 4.512) for the risk-standardized potentially preventable readmissions.

Table 24

Mean Risk-adjusted Potentially Preventable Readmission Rates Score Across the Different Years

County Name	Mean	N	Std. Deviation
Davidson	17.2	31	5.739
Hamilton	16.2	18	4.512
Knox	18.2	23	4.754
Shelby	16.7	51	4.817
Sullivan	17.2	18	4.628
Total	17.1	141	4.935

The mean risk-standardized potentially preventable readmission rates score also varied across the different years. As shown in Table 25, the highest mean risk-standardized potentially preventable readmission rate score was recorded in 2016 (24.6 ± 2.399, $n = 9$). In 2017 ($n = 33$), the mean risk-standardized potentially preventable readmission rate score was 24.0 ± 1.677. In 2021 ($n = 15$), the mean risk-standardized potentially preventable readmission rate score was 15.1 ± .670. In 2020 ($n = 24$), the mean risk-standardized potentially preventable readmission rate score was 14.3 ± 1.146. In 2022 ($n = 28$), the mean risk-standardized potentially preventable readmission rate score was 14.8 ± .852. Table 25 also shows the lowest mean risk-standardized potentially preventable readmission rate score was recorded in 2019 (12.5 ± 1.458, $n = 33$).

Table 25

Mean Risk-adjusted Potentially Preventable Readmission Rates Score Across the Different Years

Year	Mean	N	Std. Deviation
2016	24.6	9	2.399
2017	24.0	33	1.677
2019	12.5	32	1.458
2020	14.3	24	1.146
2021	15.1	15	.670
2022	14.8	28	.852
Total	17.1	141	4.935

Table 26 shows the mean risk-standardized potentially preventable readmission rates score for the rural and urban long-term care hospitals. It is evident from Table 26 that the urban long-term care hospitals (n = 105) had the highest mean score (17.1 ± 5.201) for the risk-standardized potentially preventable readmissions. Table 26 also indicates that the rural long-term care hospitals (n = 36) had the lowest mean score (16.8 ± 4.118) for the risk-standardized potentially preventable readmissions.

Table 26

Mean Risk-adjusted Potentially Preventable Readmission Rates Scores in Rural and Urban Long Term Care Hospitals

Status	Mean	N	Std. Deviation
Rural	16.8	36	4.118
Urban	17.1	105	5.201
Total	17.1	141	4.935

An independent-samples t-test was run to determine if there were differences in risk-standardized potentially preventable readmission rates scores between urban and rural long term care hospitals. The findings presented in Table 27 indicate lack of statistical significance. Therefore, there was no statistically significant difference in the risk-standardized potentially preventable readmission rates scores between urban (17.1 ± 5.201) and rural (16.8 ± 4.118) long term care hospitals (t (139) = -0.343, p = 0.732).

Table 27

Independent-Samples T-Test Showing Differences in Unadjusted Potentially Preventable Readmission Rates Scores Between Urban and Rural Long Term Care Hospitals

	F	t	*df*	Sig. (2-tailed)	95% Confidence Interval of the Difference	
					Lower	Upper
Equal variances assumed	4.952	-.343	139	.732	-2.218	1.562

A two-way ANOVA was conducted to examine the effects of year and rurality status on risk-standardized potentially preventable readmission rates scores (Table 28). Data mean ± standard deviation, unless otherwise stated. There was a statistically significant interaction between year and rurality status on risk-standardized potentially preventable readmission rates scores, $F(5, 129) = 2.441$ $p = .038$, partial $\eta 2 = .086$ (Table 28). As shown in Figure 4, the risk-standardized potentially preventable readmission rates scores were high in urban long term care hospitals compared to rural long term care hospitals in 2016 and 2017. However, from 2019 to 2022 the risk-standardized potentially preventable readmission rates scores were low in urban long term care hospitals compared to rural long term care hospitals.

Table 28

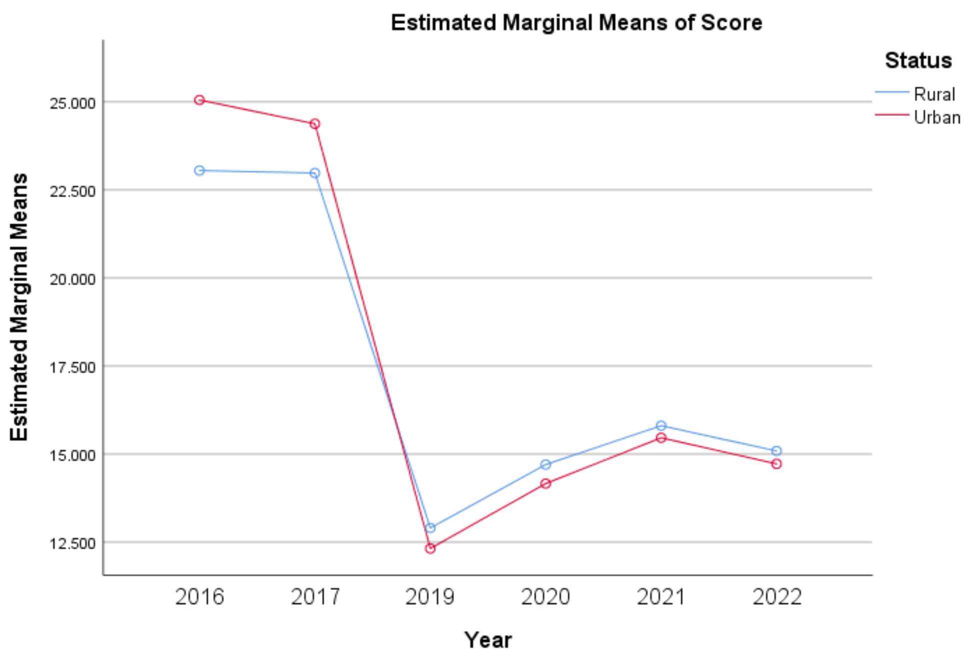
Two-Way ANOVA Showing the Effects of Year and Rurality Status on the Risk-adjusted Potentially Preventable Readmission Rates Scores

Source	Type III sum of squares	*df*	Mean square	F	Sig.	Partial Eta squared
Corrected model	3174.590[a]	11	288.599	157.948	.000	.931
Intercept	25899.971	1	25899.971	14174.887	.000	.991
Year	2092.835	5	418.567	229.079	.000	.899
Status	1.434	1	1.434	.785	.377	.006
Year * status	22.302	5	4.460	2.441	.038	.086
Error	235.705	129	1.827			
Total	44433.796	141				
Corrected total	3410.295	140				

a. *R* Squared = .931 (Adjusted *R* Squared = .925)

Figure 4

Risk-adjusted Potentially Preventable Readmission Rates Scores in Rural and Urban Long Term Care Hospitals Between 2016 and 2022



Summary

The findings presented in this chapter provide in-depth insights into the study's research question that focused on the difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge. It should be noted that the 2019 annual data was initially intended to be used to address the research question. However, due to the small sample size the decision was made to include data collected between 2016 and 2022. The study findings were obtained from the different measures of the rate of potentially preventable hospital readmissions 30 days after discharge from a long-term care hospital (L_017_01) as documented on the CMS website. The L_017_01 measures that were reported included the number of eligible stays, comparative performance, unadjusted potentially preventable readmission rate, risk-adjusted potentially preventable readmission rate and the number of potentially preventable readmissions following discharge.

Regarding the number of eligible stays, the findings indicate a drop from 2016 to 2019 followed by an increase from 2019 to 2021. The findings also show that the rural long-term care hospitals have the highest mean score for the number of eligible stays compared to the urban long-term care hospitals, and the independent-sample t-test showed that the difference is statistically significant. However, the findings showed no statistically significant interaction between year and rurality status on the number of eligible stays with the number of eligible stays being high in rural long term care hospitals compared to urban long term care hospitals across all the years. The findings also showed how potentially preventable 30-day readmission rates in the assessed long-term care hospitals are compared to the national preventable 30-day readmission rates. Although differences in the proportion of better, no different, and worse than the national rate categories were across the different years, the differences were statistically significant. There was also no statistically significant difference in the proportion of better, no different, and worse than the national rate categories between rural and urban long term care hospitals.

The findings show an increase in the unadjusted potentially preventable readmission rate scores from 2019 to 2022. Rural long-term care hospitals are also shown to have the highest unadjusted potentially preventable readmission rate mean score compared to urban long-term care hospitals. However, the independent-sample t-test showed that the difference in unadjusted potentially preventable readmission rate scores between rural and urban long-term care hospitals is not statistically significant. Similarly, the findings showed no statistically significant interaction between year and rurality status on the unadjusted potentially preventable readmission rate scores with the mean scores being high in rural long term care hospitals compared to urban long term care hospitals across all the years. The findings also show that the rural long-term care hospitals have lower risk-standardized potentially preventable readmission rate mean scores compared to the urban long-term care hospitals. However, the independent-sample t-test showed that the difference in risk-adjusted potentially preventable readmission rate scores between rural and urban long-term care hospitals is not statistically significant. But the findings showed a statistically significant interaction between year and rurality status on the risk-adjusted potentially preventable readmission rate scores with the mean scores being high in urban long term care hospitals compared to rural long term care hospitals in 2016 and 2017 and being lower in 2019 to 2022.

Concerning the potentially preventable readmissions following discharge, the findings show an increase from 2019 to 2021. The findings also suggest that rural long-term care hospitals have the highest potentially preventable readmissions following discharge mean score compared to urban long-term care hospitals. The independent-sample t-test showed that the difference is statistically significant. However, the findings showed no statistically significant interaction between year and rurality status on the potentially preventable readmissions following discharge scores with the mean scores being high in rural long term care hospitals compared to urban long term care hospitals across all the years.

Therefore, the findings indicate that for the number of eligible stays, comparative performance, and the unadjusted potentially preventable readmission rate, there is no statistically significant difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge. However, considering the number of potentially preventable readmissions following discharge, there is a statistically significant difference between urban and rural long-term care hospitals in Tennessee in the rate of potentially preventable hospital readmissions 30 days after discharge. For the case of risk-adjusted potentially preventable readmission rate, there is a statistically significant difference between urban and rural long-term care hospitals only if the interaction between year and rurality status is considered. In section 4, a comprehensive interpretation of the presented findings is provided along with the limitations, recommendations, and implications.

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

Introduction

The purpose of this quantitative descriptive study was to determine whether there are differences in 30-day readmission rates among the elderly between urban and rural long-term care hospitals in Tennessee. The study used hospital location as the independent variable, categorized as urban or rural, and the 30-day admission rates as the dependent variable, measured on a continuous scale. Gender and insurance coverage were considered as covariate variables. The study employed a quantitative approach guided by a descriptive design that involved the analysis of data collected the period from 2016 to 2022. This study was conducted to address the existing gap in understanding the disparity in 30-day readmission rates among the elderly in urban and rural long-term care hospitals. The study outcome provides updated information to relevant stakeholders regarding readmissions within 30-day period urban and rural long-term care hospitals in Tennessee and the insights that contribute to the reduction of 30-day readmission rates. In summary, there was no statistically significant difference between urban and rural long-term care hospitals in Tennessee in terms of the number of eligible stays, comparative performance, and unadjusted potentially preventable readmission rates. However, there was a significant difference in the rate of potentially preventable readmissions following discharge, and for risk-adjusted potentially preventable readmission rates, the difference was significant only when considering the interaction between year and rurality status. In Section 4, I provide a comprehensive interpretation of the study findings, along with limitations, recommendations, and implications.

Interpretation of the Findings

There are various methodological issues that need to be taken into consideration when interpretating the findings of this study. One of the important issues is the decision to include data collected between 2016 and 2022 instead of the only the 2019 annual data, as was initially intended. The use of 2016–2022 ensured that the study included the 2022 data showing current situation and the additional data that helped in determining the changes overtime. Therefore, the data used helped in overcoming the common currency-related challenges associated with the use secondary data, thereby promoting currency and timeliness of the study and potentially enhancing the applicability of the research findings (Kraska et al., 2015).

Study results suggested that the rural long-term care hospitals have the higher number of eligible stays compared to urban long-term care hospitals. The outcome of this study also indicates a fluctuation in the number of stays over time with recent trend (from 2019 to 2021) showing an increase in the number of eligible stays. The higher number of eligible stays in the rural long-term care hospitals give insights increased healthcare utilization patterns and disease burden among the elderly in the rural settings (Jiang et al., 2010). It should be noted that various researchers support the view that the rural elders experience poor health and increased risk of death compared to urban elderly which could be attributed to the barriers to healthcare access (Garcia et al., 2019; Schreckinger et al., 2021). The results of the study could be also due to the significant health challenges faced by rural American populations, which could be associated with limited access to health and health coverage (Foutz et al., 2017).

The study findings also indicated that rural long-term care hospitals have a higher mean number of potentially preventable readmissions following discharge compared to urban long-term care hospitals. The statistical analyses confirmed the significant difference between the two groups. Additionally, there was no significant interaction between year and rurality status, suggesting that the reporting difference in the number of potentially preventable readmissions between the rural and urban long-term care hospitals was not influenced by the year. It should be noted that potentially preventable readmissions could be used to indicate problems with quality of care (Meurs et al., 2021; Rubin et al., 2017; Wish, 2014). Therefore, the outcome of this study suggests possible issues with quality of care in rural long-term care hospitals due to higher number of potentially preventable readmissions (Goldfield et al., 2008; Meurs et al., 2021; Rubin et al., 2017; Wish, 2014). However, the observations indicating higher number of potentially preventable readmissions in the rural long-term care hospitals contradicts the conclusions made by Murray et al. (2021).

Considering the Donabedian theoretical model, the findings suggest the difference in the various aspects of the readmission rates between urban and rural long-term care hospitals in Tennessee could be related to the difference in the existing structures and processes. Considering the various aspects of the readmission rates as the outcome (Ibanez, 2021; McCants et al., 2019; Swilling, 2020), the difference in number of potentially preventable readmissions and eligible stays suggests that variation in the structures and processes among urban and rural long-term care hospitals. However, in this study, the specifics regarding the structures including hospital’s facility, qualifications of care providers, human resources, accounting, and material resources and processes such as how the healthcare system work, were not studied (Donabedian, 1966).

Limitations of the Study

In this section, the limitations associated with the study are explained, which is crucial for appropriately interpreting and contextualizing the obtained findings (Theofanidis & Fountouki, 2018). The two major limitations associated with this study is the use of archival data and the adopted quantitative methodological approaches. The highlighted limitations impact on the generalizability, applicability, validity, and reliability of the study findings. Reliability, which describes the extent to which the findings are consistency and stable could have been impacted negatively using archival data that might have been collected for other purposes. Given that I had no control over the data collection process, it was not possible to address inherent inconsistencies or missing information in the archival data, which affect the reliability of the study's conclusions (Jones, 2010).

The use of archival data in this study also raises concerns regarding the validity of the reported findings and study conclusions. First, issues associated with accuracy and completeness of the archival data are of concern. Secondly, there are concerns regarding the time-bound nature of the data and the differences or unique contextual settings including historical, social, or institutional that could make the archival data less valid or outdated. I had no means of discounting the possible occurrence of selection bias, which also raises concerns regarding the validity of the study findings (Jones, 2010).

There are also concerns regarding the impact of the use of the archival data on the generalizability of the study findings and conclusions. Using archival data that focused on a specific period could impact negatively on the extent to which the study's findings could be generalized to a broader context (Jones, 2010). The concerns emerge from the view that the findings from such the analysis of such data does not reflect the current dynamics or account for potential changes in hospital readmissions, such as those related to the COVID-19 pandemic.

Recommendations

In this section, the recommendations for future research are provided. These recommendations emerge from the limitations associated with archival data, quantitative methodologies, and outdated information. The recommendations also emerge from the gaps the arise from study findings are as follows:

1. Future research should address the limitations associated with the use of archival data. For example, researchers should explore alternative data sources such as primary data sources to enhance the reliability, validity, and generalizability of the findings.
2. Future research should also consider the limitations associated with the adopted quantitative methodological approach. This goal could be accomplished by exploring alternative methodological designs especially the mixed methods to gain a more comprehensive understanding of the topic. The mixed methods incorporate qualitative approaches that take into consideration the contextual aspects.

3. Future researchers need to focus on the factors that contribute to the higher number of eligible stays and potentially preventable readmissions in the rural long-term care hospitals compared to the urban long-term care hospitals. The future studies should consider the existing structures and processes within the rural and urban long-term care hospitals as proposed by Donabedian theoretical model.

Implications for Professional Practice and Social Change

The study outcome is associated with important professional practice implication. The findings of the study provide insights into the 30-day readmission rates, which guide the steps that could be taken to enhance the care quality and reduce healthcare costs in urban and rural long term care hospitals (Rubin et al., 2017). As noted from this study, the number of eligible stays and potentially preventable readmissions are higher in rural long-term care hospitals compared to urban long-term care hospitals. Therefore, there is a need to enhance the hospital processes and practices in the rural long-term care hospitals. The approaches that could be taken include improving care coordination, timely access to healthcare services, preventive care, context-specific interventions, and data-driven quality improvement to address the higher number of eligible stays and potentially preventable readmissions in rural long-term care hospitals.

The study findings offer valuable theoretical implications. I acknowledge the limitation of not examining the specifics of the structures and processes comprehensively, as documented in the Donabedian theoretical model. Therefore, there is a need to further examine the Donabedian theoretical model’s structures and processes of urban and rural long-term care hospitals. By understanding the intricate interplay between the structures and processes, researchers can develop a more comprehensive theoretical understanding of how they impact readmission rates and contribute to the overall quality of care in the urban and rural long-term care hospitals.

The outcomes are associated with important positive social change implications. The findings suggest higher readmission rates in rural long-term care hospitals compared to urban settings provide valuable insights for driving positive social change in healthcare. Since the findings point to concerns regarding the quality of care and cost of care among the elderly in rural long-term care hospitals compared to those in urban, the study advocates addressing factors to improve quality of care and cost of care for the affected population. If shared with healthcare administrators, the findings could prompt the relevant stakeholders to address disparities, enhance healthcare infrastructure, improve care coordination, and adopt specific policies that will enhance the healthcare outcomes for elderly in rural long-term care hospitals, leading to reduced readmission rates. Reduced readmission rates could contribute towards reduced healthcare expenditure and avail resources towards economic development.

Conclusion

This study has provided insights into the differences in 30-day readmission rates among the elderly that exist between urban and rural long-term care hospitals in Tennessee. Based on the 2017–2020 data on 30-day readmissions obtained from the CMS, there is a higher number of eligible stays and potentially preventable readmissions in the rural long-term care hospitals compared to the urban long-term care hospitals. The study findings prompt the stakeholders to consider interventions that could improve quality care among the elderly specifically in Tennessee's rural areas to reduce the number potentially preventable readmissions. The findings also prompt future researchers to further assess the healthcare processes and structures responsible for the reported higher number of potentially preventable readmissions in the rural long-term care hospitals.

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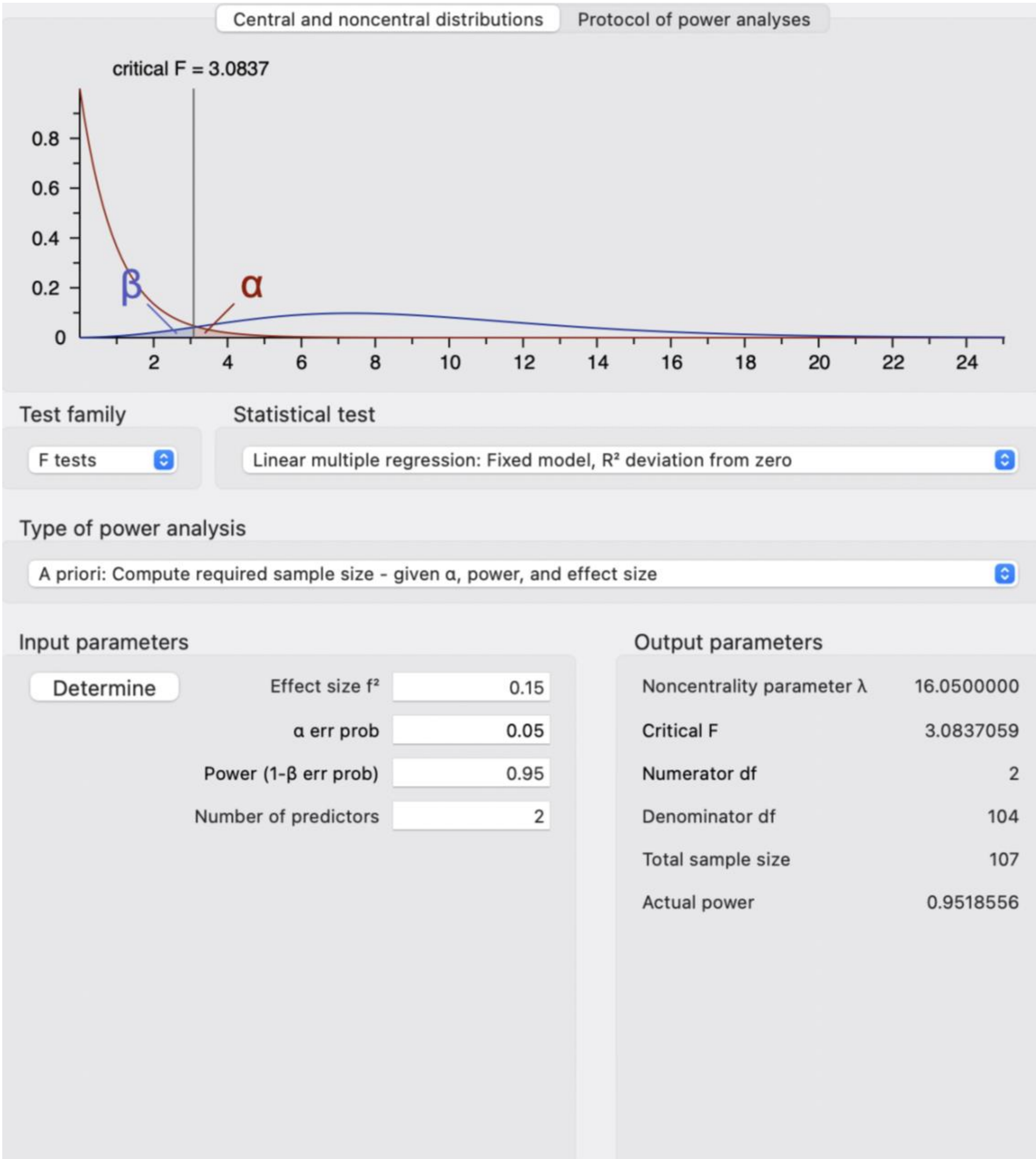
Appendix A: Sample Size (Multiple Linear Regression)



Appendix B: Sample Size (Independent Sample T-test)